2016

Advanced Electronic Health Records (EHR) and Their Impact on Medication Errors

Steven Goriah
Medical University of South Carolina

ADVANCED ELECTRONIC HEALTH RECORDS (EHR) AND THEIR IMPACT ON MEDICATION ERRORS

By

Steven Goriah

A doctoral project submitted to the faculty of the Medical University of South Carolina in partial fulfillment of the requirements for the degree of Doctor of Health Administration in the College of Health Professions

ADVANCED ELECTRONIC HEALTH RECORDS (EHR) AND THEIR IMPACT ON MEDICATION ERRORS

By

Steven Goriah

Approved by:

Abby Kazley	Abby Kazley, PhD	4/20/16
Chair, Project Committee		Date
Karen A. Wager	Karen A. Wager, DBA	4/22/16
Member, Project Committee		Date
Scott Stickles, DO	Scott Stickles, DO	4/14/16
Member, Project Committee		Date
Lisa Saladin	Lisa K. Saladin, PT, PhD	4/25/16
Dean, College of Health Professions		Date

ACKNOWLEDGEMENTS

There are so many who have helped me get to this point, thanking only a few will not express the extent of my sincerest gratitude for all who have played a part. My inspirations for everything I do are my two sons Ethan and Evan, and this was no different. To them I say, the love and joy you bring is what drives me, and I am forever grateful to have the honor of being your father.

To my most loving and dedicated wife Sharon, I am humbled by your kindness, understanding, and support you offer for everything I do. To my mother, who has given everything so I can succeed, words cannot express how grateful I am to you.

To my project committee, Dr. Karen Wager and Dr. Scott Stickles and most especially Dr. Abby Kazley, I offer my most heartfelt gratitude for all your help and support throughout this project. I would also like to recognize Dr. Kit Simpson, whose wisdom and guidance was instrumental to my success throughout the program. Lastly, I would like to thank Mr. Paul Beharry for his unwavering support and encouragement along this journey.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Abstract of Doctoral Project Report Presented to the Executive Doctoral Program in Health Administration & Leadership
Medical University of South Carolina
In Partial Fulfillment of the Requirements for the
Degree of Doctor of Health Administration

ADVANCED ELECTRONIC HEALTH RECORDS (EHR) AND THEIR IMPACT ON MEDICATION ERRORS

By
Steven Goriah
Chairperson: Abby Kazley, PhD
Committee: Karen A. Wager, DBA
Scott Stickles, DO

Abstract

A review of the literature revealed the need for further analysis of the impact of advanced electronic health record (EHR) use on medication error rates within US hospitals. A retrospective cross-sectional patient level analysis using the combined 2009 data from the National Inpatient Sample (NIS), Health Information Management Systems Society (HIMSS) Analytics, and American Hospital Association (AHA) annual survey datasets was conducted to study the relationship between advanced electronic health record use and medication error rates.

A random sample of 1,032,905 patient cases was selected. A total of 301,289 (29.2%) patient cases originated from hospitals with advanced EHR. A total of 550 hospitals were included in the analysis, with 104 (18.9%) reporting use of advanced EHR. Compared to patient cases from hospitals without advanced EHR, those with advanced EHR had a lower proportion of medication errors (6.7% vs. 6.3%, $p < 0.0001$). There was only a small difference in the assumed direction to begin with, but it remained when using the propensity score stratification although the association was no longer

statistically significant when using the matched sample. This indicates that the small statistically significant difference revealed in the initial analyses may have been due to selection bias. While use of advanced EHRs has great potential for improving a variety of health and safety matters in the hospital, it is possible that its current implementation has not evolved enough to have an effect. Technology alone will not solve the problem, but it can be a part of the solution. We must establish a total systems approach to problem of patient safety where technology is part of the solution.

CHAPTER 1

INTRODUCTION

Background and Need

Patient safety has emerged as a central measure of quality in today's healthcare environment that has far-reaching impact on various aspects in the continuum of care. The practice of patient safety has been defined as those practices that reduce the risk of adverse events related to exposure to medical care across a range of diagnoses or conditions (Shojania et al., 2001). The Institute of Medicine (IOM) defines patient safety as the prevention of harm to patients (Berkowitz et al., 2012) and places it under the overarching umbrella of quality measures in healthcare (Kohn et al., 2000). Emphasis is placed on the system of care delivery that (1) prevents errors, (2) learns from the errors that do occur, and (3) is built on a culture of safety that involves health care professionals, organizations, and patients (Aspden, 2004). The Agency for Healthcare Research and Quality's (AHRQ) Patient Safety Network website expands upon the definition of prevention of harm, describing it as freedom from accidental or preventable injuries produced by medical care (AHRQ, 2007).

IOM conducted a landmark study in 1999 on medical errors and found that medical errors lead to the deaths of between 44,000 and 98,000 people in US hospitals each year (JHITA, 2000). The *Journal of the American Medical Association* gives a more conservative estimate and states that between 5,000 and 15,000 of those deaths were

preventable (Gillespie, 2002). One type of medical error is adverse drug events (ADEs), which are a subset of those injuries associated with errors that occur during the ordering, administering, dispensing, and monitoring of drugs (Wolfstadt et al, 2008). ADEs increase morbidity, and health care costs.

In addition to their impact on patient mortality, ADEs exact other significant costs. They have been estimated to result in higher costs due to additional care necessitated by the errors, lost income and household productivity, and disability of between $17 billion and $29 billion per year in hospitals nationwide (JHITA, 2000). The impact of medication errors is also felt when patients lose trust in the health care system and when both patients and health professionals experience reduced satisfaction. Patients who experience a long hospital stay or disability as a result of errors experience physical and psychological discomfort. Health professionals pay with loss of morale and frustration at not being able to provide the best care possible. Society bears the costs of errors as well, in terms of lost worker productivity, reduced school attendance by children, and poorer population health (Kohn et al., 2000).

A number of factors contribute to medication errors. One of the most challenging but preventable factors is the decentralized and fragmented nature of the healthcare delivery system. When patients see multiple providers in different settings, none of whom have access to complete information, it becomes easier for errors to occur (Kohn et al., 2000).

Historically, most third-party purchasers of healthcare provided little financial incentive for health care organizations and providers to improve safety and quality (Kohn

et al., 2000). Pay for Performance is changing the way Medicare pays for hospital care by rewarding hospitals for delivering services of higher quality and higher value (Cromwell et al., 2011). The program is an umbrella term for initiatives aimed at improving the quality, efficiency, and overall value of health care. In some Pay for Performance models, payers consider information technology critical to improving the coordination, quality, and efficiency of care. In such a measure, payers might reward organizations for the use of an EHR to order prescriptions for their patients, a process that can both lower costs and improve quality by reducing medication errors (Cromwell et al., 2011).

Many patient safety practices that are tied to information technology, such as use of simulators, bar coding, computerized physician order entries, and crew resource management, which have been considered as possible strategies to avoid patient safety errors and improve healthcare processes. Although not all adverse events in healthcare are preventable, IOM concluded that many could be avoided through better professional practices, more effective teamwork, and new technology (Berkowitz et al., 2012). EHRs that use computerized physician order entry (CPOE) with clinical decision support (CDS) have been promoted as an effective strategy to prevent the development of a drug injury defined as an adverse drug event (ADE) (Wolfstadt et al., 2008). CDS is a technology that provides clinicians with real-time feedback about a wide range of diagnostic and treatment-related information as they are entering electronic orders. By running electronic rules in the background, decision support can check for a variety of potential errors such as drug interactions, patient allergies to prescribed medications, medication contraindications, and renal- and weight-based dosing. For a number of years,

organizations such as the Institute of Medicine and Leapfrog have been calling for implementation of advanced EHRs, and CPOE in particular, (Milstein et al., 2000).

Efforts have been underway for nearly 50 years to implement EHR systems. The pace of change has greatly accelerated since the passage of the Health Information Technology for Economic and Clinical Health Act (HITECH) which is part of the American Reinvestment & Recovery Act (ARRA) of 2009. This is an effort to transform healthcare delivery through widespread adoption and use of EHR technology. Meaningful Use is an incentive program authored by the Centers for Medicare & Medicaid Services (CMS) that provides eligible hospitals and professionals with financial incentives to implement EHR systems and demonstrate "meaningful use" of certified systems.

HITECH proposes the meaningful use of interoperable EHRs throughout the health care delivery system as a critical national goal. The concept of Meaningful Use rests on five pillars of health outcomes policy priorities, namely: (1) improving quality, safety, efficiency, and reducing health disparities; (2) engaging patients and families in their own healthcare, (3) improving care coordination, (4) improving population and public health, and (5) ensuring adequate privacy and security protection for personal health information (CMS.gov).

By providing incentives to individual providers for using EHR systems in specific ways, CMS has motivated a fragmented customer base to behave more like a single customer with coherent demands. In effect, CMS, as a behind-the-scenes customer, is driving standardization and the resulting economies of scale and scope in the EHR field

in the same way that large industry players have been able to standardize and draw value from IT use in banking, retail merchandising, airlines, food services, and other sectors of the economy. Understanding that markets are often slow to respond to customer demand, and that EHR purchasers have limited ability to evaluate the quality of EHR vendor products prior to purchase, HITECH also created federal certification of EHR products. This certification gives a degree of assurance to providers and CMS about the quality of EHR products they purchase (healthit.gov).

The Meaningful Use incentive program was established with three phases: Stage 1, Data Capture and Sharing; Stage 2, Advanced Clinical Processes; and Stage 3, Improved Outcomes (see Table 1). Stage 1 of the Meaningful Use program focuses primarily on promoting consistency of documentation in terms of what data should be captured (content) and how it should be presented (structure). It does not address in detail how data should be recorded (vocabulary) (healthit.gov). Stage 1 also links documentation requirements with measurement and decision support requirements to ensure that the data being captured are more than just a description of observations, diagnoses, and treatments for future reference; clinicians now had the systems and the motivation to document in ways that would allow EHR systems to be tools for enhanced decision-making.

In terms of interoperability of systems, Stage 1 focuses on promoting inter-organization electronic transactions that were already gaining acceptance in the market, such as e-prescribing, lab results delivery, and public health reporting. It also laid the foundation for new types of transactions, specifically EHR-to-EHR transactions, by requiring that systems be able to generate electronic record extracts that can be read by

other systems. The ability to electronically send, receive, and incorporate such extracts from other EHR systems was left for more advanced stages.

In Stage 2, Meaningful Use requires hospitals and health care providers to meet more advanced requirements to qualify for incentives during this stage, and specifies what criteria electronic health records must meet to achieve certification. Specific to Stage 2, the capability to submit electronic data about immunizations is in the core set of criteria for eligible professionals (EPs), as are the capability to submit electronic data for immunizations, reportable laboratory results, and syndromic surveillance. In addition, two new public health objectives for EPs have been added to the menu set, requiring the capability to 1) identify and report cancer cases to a cancer registry and 2) identify and report non-cancer cases to specialized registries.

Stage 2 further refines the notion of system-neutral records by taking EHR-to-EHR interoperability further and requiring not just common structures (consolidated Clinical Document Architecture (CDA)) and common content (problems, labs, medications, etc.), but use of specific vocabularies as well, such as SNOMED CT, LOINC, and RxNORM, to enable cross-system understanding of clinical information from one organization to another. And while Stage 1 simply requires that systems be able to generate standardized clinical documents, Stage 2 requires that they be able to transport clinical information from one system to another.

Stage 3 rules were announced in October 2015, making significant changes intended to ease the reporting burden on all providers, support health information

exchange, and improve patient outcomes. One important change is a shift in focus so that health IT becomes a tool for care improvement, not an end in itself.

While each stage of Meaningful Use has sent ripples of change across the EHR landscape in terms of functions and capabilities, each stage has also engendered evolution in the very definition of an EHR. While Meaningful Use is not yet complete, it is not too early to assess how it is already shaping the field. Setting common functional requirements for EHRs and incentives for users to take advantage of those functions, the Meaningful Use program has imposed a degree of coordination on healthcare that the fragmentation of the industry has prevented up until now. Meaningful Use can go only so far, however, as it is not robust enough to change larger and deeper trends in the industry that are driving business arrangements and revenue models.

Meaningful Use has certainly been successful in creating a common floor of capability across vendors' systems, which has inalterably shaped the EHR industry. It has also had a profound impact on the widespread adoption and use of EHR systems in hospitals and physician practice.

Vendors have yet to reach plug-and-play capability with EHR systems, however, and it is highly unlikely that Meaningful Use will have enough influence or enough time to instill such capability in the market.

Problem Statement

There has been little research on the overall effectiveness of advanced EHRs on medication errors in an inpatient setting. Various studies have attempted to show the value of various aspects of technology on patient care, but no comprehensive research

had been conducted to evaluate the relationship between advanced EHR use and medication errors among US hospitals. This study has sought to understand the relationship between advanced EHR use and medication errors in US hospitals participating in HIMSS Analytics, a global, cause-based, not-for-profit organization promoting better health through information technology (IT).

Research Question

What is the relationship between advanced EHRs use and medication errors rates in HIMSS Analytics participating US hospitals?

Hypothesis

Hypothesis: Hospitals with advanced EHRs have lower rates of medication errors compared to hospitals without advanced EHRs.

EHR Adoption Model

EHRs in our sample was grouped by stage of use, a model previously used by Kazley (2014), based on individual application reported to be in use by the hospitals The EHR usage level was classified into four stages based on various components of an EHR reported to be in use at the time of reporting. These measures were grouped into categories to measure the level EHR functionality of each hospital in its EHR journey (see Table 1). This allowed us to measure the effects on medication error rates for each hospital as the hospital adopts additional components of an EHR. The categories we used are Stage 0 (no EHR applications installed), Stage 1 (EHR with ancillary services including a clinical data repository, pharmacy, laboratory, and radiology information systems), Stage 2 (Stage 1 plus EHR with nursing workflow including electronic nursing

documentation and medication administration records), and Stage 3 (EHR with Stage 1 and 2 components, plus CPOE and clinical decision support). A hospital with Stage 3 EHR has reported successful implementation all of all Stage 1 and Stage 2 applications plus CPOE and CDS. Teufel et al. (2012) point out that many of the functions present in advanced Stage 3 would be considered minimal functions required to meet Meaningful Use objectives. Since Stage 3 consists of more advanced automated features, Stage 3 hospitals should possess enhanced capabilities to handle the demands of providing high quality care, which in turn will affect the patient safety capabilities of those hospitals.

Sample

The sample size was a 20% random sample of patients from hospitals using the combined 2009 data from the National Inpatient Sample (NIS), HIMSS and AHA datasets. The patients in our sample were grouped by stage of use of EHR at their associated hospitals, a model previously used by Kazley (2014), based on individual application reported to be in use by these hospitals in our sample.

Definitions

Key definitions in this research study are:

1. ADE: Adverse Drug Events
2. Advanced EHR: Advanced EHR will be classified as a hospital that has met Stage 3 criteria for EHR adoption and use.
3. ARRA: The American Reinvestment & Recovery Act.
4. CDS: Clinical Decision Support
5. CPOE: Computerized Provider Order Entry

6. HITECH: The Health Information Technology for Economic and Clinical Health Act.
7. ME: Medication Error

CHAPTER 2

REVIEW OF THE LITERATURE

A comprehensive review of the available literature was conducted on previous studies whose topics directly related to the research topic. Studies that focused on the technology in healthcare were reviewed for their impact on the quality and safety of healthcare. We concluded our literature review by reviewing studies relating to meaningful use and EHR adoption to understand prior work and how it will impact this study.

Patient Safety (Medication Errors)

Approximately one quarter of all adverse events that occur in hospitals are adverse drug events or medication-related errors (Covell & Ritchie, 2009). Although healthcare providers have ethical and professional obligations to disclose adverse events, medication errors continue to be underreported. Consequently, little is known about the types of medication errors that are not reported.

In *To Err is Human*, a 2002 study published by the Institute of Medicine (IOM), Kohn et al. (2000) estimate that as many as 98,000 people die per year from medical errors that occur in hospitals. Shojania et al. (2001) reviewed previously published studies to understand existing evidence on practices relevant to improving patient safety. They concluded that practices with the strongest supporting evidence are generally clinical interventions that decrease the risks associated with hospitalization, critical care,

or surgery. They also found that many patient safety practices drawn primarily from nonmedical fields (e.g., use of simulators, bar coding, computerized physician order entry, and crew resource management) deserve additional research to illuminate their value in the health care environment.

Varkey & Bisping (2007) conducted a prospective trial on 104 primary care patients at the Mayo Clinic to investigate how to improve medication reconciliation and increase patient safety. Patients in Phase I received standard care. Patients in Phase II received the intervention reconciliation process, which consisted of (1) mailing letters before appointments to remind patients to bring medication bottles or updated medication lists to their visits, (2) verifying medications, and (3) correcting the medication list in the electronic medical record by the patient, and academic detailing and weekly audit and feedback of performance. They found that interventions resulted in an 89% decrease in prescription medication errors in Phase I and a 66% decrease in Phase II. Decreases in errors from 98% of the visits in Phase I to a decrease of 84% of the visits in Phase II were documented. When all medications were considered, a 98% decrease in medication errors was documented in Phase I, as well as an 84% decrease in Phase II. The average number of discrepancies per patient decreased by more than 50%, from 5.24 in Phase I to 2.46 in Phase II.

To reduce the occurrence of medication-related errors, the Institute of Medicine (IOM) recommends implementing health information technologies in conjunction with other process improvements programs such as clear communication of drug information between the provider and patient, a team-based approach that demands the attention of

everyone involved, and encouraging the accrediting agencies to require training in medication management practices (Aspden, 2006).

Healthcare Information Technology.

Computerized Provider Order Entry (CPOE) are electronic orders for medication, laboratory and radiology services placed by a licensed healthcare professional into the Electronic Health Record (EHR) per state, local and professional guidelines. In using CPOE for medications, orders are incorporated with patient information, such as other prescriptions and lab results, which can be automatically checked for potential errors or problems. This real-time crosscheck improves optimal drug selection and reduces errors at the time of ordering, a safer and more effective way to order medications than using prescription pads or paper forms. Researchers found that 90 percent of all providers felt that the VA electronic prescribing system, including its order check, improved prescribing safety to some degree (Spina et al., 2011). It reduces the chance of selecting medications for which the patient has a known allergy, or drugs that are off-formulary for their health plan. Additionally, the medication information is updated in the patient's medical record and easily available for follow-up visits. Birkmeyer (2004) estimates that universal implementation of CPOE would avert approximately 567,000 serious medication errors each year in the United States.

While not all adverse events in healthcare are preventable, IOM concluded that many could be avoided through better professional practices, more effective teamwork, and new technology (Berkowitz, 2012). When implemented together, CPOE systems and CDS can improve medication safety and quality of care and reduce costs of care (Kaushal, 2003). The CPOE system employed a CDS element to provide clinicians with

access to evidence-based guidelines, prompts, and alerts at the bedside. CPOE should not be pursued in isolation from other technologies. Simply entering orders in a system without providing clinical decision support during the order-entry process may have limited benefit. In order to optimize impact on quality, safety, and efficiency, CPOE should be an integrated component of the EHR system. They can also improve compliance with provider guidelines, as well as the efficiency of hospital workflow (Dexter, 2001). Most evidence demonstrating the value of CPOE comes from research in hospital settings. CPOE and decision support systems (DSS) can reduce certain types of error (Handler et al., 2004).

The results from a case study conducted at the University of Maryland in 2006 on continuous medication infusion in a pediatric ICU showed the benefit of using CPOE versus handwritten orders. The results indicated that a total of 234 orders were generated using each method by 26 physicians ordering nine drips each. Orders placed using CPOE required significantly less time (5.5 minutes + 2 minutes) as compared to the handwritten method (26 minutes + 8 minutes). In addition, use of CPOE resulted in significantly fewer errors: 10 of 243 drip orders (4.3%), compared to the handwritten method, where 170 of 243 drip orders (73%) contained one or more errors. Among the handwritten errors, 25% were judged to be ‘high-risk’ with the potential for serious adverse effects (Vaidya, 2006).

In a 2012 study, Dow et al. studied the impact of implementing CPOE on three elements of medication use system performance: inpatient medication override dispense rates from automated dispensing cabinets (ADCs), medication first-dose turnaround time (TAT), and pharmacists’ perceptions of the medication orders management process.

Their results support the positive effects of an advanced EHR on patient safety, indicating that after the implementation of CPOE, the relative number of medication override dispenses decreased by 58%. The mean time from order entry to order verification improved by 76%, and the mean TAT for intravenous antibiotics improved by 31%. Pharmacists' overall satisfaction with the medication orders management process improved by 23%. Dow et al. concluded that the implementation of CPOE resulted in improvement in each of the three medication use system elements assessed.

A cross sectional nationwide study conducted with Veteran Administration (VA) physicians on the perceptions of and experiences with order entry and order checks (drug alerts) in an electronic prescribing system may help improve medication safety technology. This study also shows systems using an advanced EHR can have a positive impact on patient safety. Researchers found that 90% of all providers felt that the VA electronic prescribing system, including its order check, improved prescribing safety to some degree. A significant number (88%) of physicians who encountered serious allergic or adverse drug reactions reported either notifying a pharmacist or entering the information in the allergies/adverse reactions field, and 48% of providers described critical drug-drug interaction alerts as very useful (Spina et al., 2011).

Wolfstadt et al. (2008) conducted a cross-sectional retrospective study on the impact of CPOE with CDS on adverse drug event. The Wolfstadt study is significant to this study in that of the nine studies that were evaluated in a hospital setting (One study was done on an ambulatory care setting.), only three were conducted with hospitals with COPE with CDS implemented house-wide. The Wolfstadt review only included three

studies that used commercially sold systems, whereas seven studies used in-house designed systems.

Evans et al. (1994) evaluated the prevention of ADEs with a computer alert program that provided alerts of drug allergies at the time of drug ordering. The study used a quasi-experimental pre/post design and found a significant reduction in the rate of ADEs due to allergic reactions from 56 in the one-year baseline period to 8 and 18 during two subsequent one-year study periods that incorporated CPOE with CDS ($P < .002$). There were no ADEs in years two and three of the study involving patients whose drug allergies were known and displayed, compared with 13 in the first year, when known drug allergies were not displayed. Severe ADEs were significantly reduced from 41 in the first study period to 12 and 15 during the two CPOE implementation periods ($P < .001$)

Bates et al. (1998) assessed the effectiveness of CPOE with CDS for reducing preventable ADEs and demonstrated a reduction in the rates of both total ADEs and preventable ADEs per 1,000 patient-days. The trend in total ADEs non-significantly fell from 14.7 to 9.6 between the baseline and the third study period ($P = .09$), and the trend in preventable ADEs significantly decreased from 2.9 in the baseline period to 1.1 in the third study period ($P = .05$). The investigators reported a non-significant reduction of 17% in preventable ADEs during the intervention period ($P = .37$). This is significant for our study, which will focus on preventable ADEs, in that an advanced EHR that includes CPOE with CDS may have a greater impact on preventable ADEs such as medication errors than one without it.

In 2011 Zlabek et al. studied the early cost and safety benefits of an inpatient EHR, in an inpatient setting. The study was conducted at Gundersen Lutheran Medical Center, a community-based tertiary referral center and teaching hospital with 325 licensed beds and a Level 2 trauma center. During this retrospective longitudinal study, data were collected for the period one year before EHR (pre-EHR) and one year post-EHR implementation. Measures of cost of care, safety, and quality for which data were readily available pre-EHR and post-EHR were selected and captured for all hospitalized patients. Their results are as follows: Medication errors per 1000 hospital days decreased from 17.9 to 15.4 (14.0%; $p < 0.030$), while near misses per 1000 hospital days increased from 9.0 to 12.5 (38.9%; $p < 0.037$), and the percentage of medication events that were medication errors decreased from 66.5% to 55.2% ($p < 0.007$).

Jayawardena (2007) conducted a retrospective study at a Brooklyn, NY hospital to evaluate the efficacy of a CPOE system with the help of ancillary support in minimizing prescription errors. They categorized the errors as inappropriate dosage adjustment for creatinine clearance, duplication, incorrect orders, allergy verification, and incomplete orders. The pharmacists identified the type of error, the severity of error, the class of drug involved, and the department that made the error. A total of 466,311 prescriptions were entered during the period of one year, and 3513 errors were identified during this period (7.53 errors per 1000 prescriptions). More than half of these errors were made by the internal medicine specialty. In this study, 50% of the errors were severe errors (overdosing medications with narrow therapeutic index or over-riding allergies), 46% were moderate errors (overdosing, wrong dosing, duplicate orders, or prescribing multiple antibiotics), and 4% were not harmful errors (wrong dosing or

incomplete orders). The errors were also categorized according to the class of medication. Errors in antibiotic prescription accounted for 54% of all errors. The pharmacist detected all of these prescription errors as the prescriptions were reviewed in the CPOE system. Jayawardena (2007) noted that prescription errors are common and found that the CPOE system can prevent and alert the prescriber and pharmacist to dosage errors and allergies. Involvement of the pharmacist in reviewing the prescription and alerting the physician has minimized prescription errors to a great degree in this hospital setting (Jayawardena, 2007).

Studies have shown EHR implementations, especially CPOE, have a positive correlation to the reduction of medication errors (Birkmeyer, 2004). The safe use of medications is an important area of concern within health care. On its own, CPOE has an impact on safety by ensuring that orders are legible, yet the value of this functionality is increased by adding clinical decision support (CDS) systems (Kuperman, 2003). CDS is a technology that provides clinicians with real-time feedback about a wide-range of diagnostic and treatment-related information as they are entering electronic orders. By running electronic rules in the background, decision support can check for a variety of potential errors. Examples include drug interactions, patient allergies to prescribed medications, medication contraindications, and renal- and weight-based dosing. An advanced EHR with features such as CPOE with electronic prescribing, drug interaction alerts, and information sharing among providers via exchanges can lead to a reduction in adverse events. Leapfrog also estimates that universal implementation of CPOE would avert approximately 567,000 serious medication errors each year in the United States (Birkmeyer, 2004).

Meaningful Use and EHR Adoption

The Electronic Health Record (EHR) adoption rate has increased significantly over the past few years. 78 percent of office-based physicians report that they have adopted some type of EHR system. About half of all physicians (48 percent) had an EHR system with advanced functionalities in 2013, a doubling of the adoption rate in 2009, and about 59 percent of hospitals had adopted an EHR system with certain advanced functionalities in 2013, quadrupling the percentage for 2010 (HHS Press, 2014).

To attain the full effect of an advanced EHR, adoption is critical in both hospital and physician practice setting. President Obama, following in his predecessor's footsteps, first declared the goal of near universal EHR use by 2014. In the early stages of the EHR incentive program, approximately ten percent of hospitals and 20 percent of physicians were using these systems, and even fewer could meet the preliminary definition of meaningful use. Adoption of EHRs has been increasing at about three percent to six percent per year (Jha, 2010), and the widespread use of EHRs in the United States is inevitable. EHRs will improve caregivers' decisions and patients' outcomes (Blumenthal & Tavenner, 2010). There is wide consensus regarding the potential of health information technology, especially the EHR, to improve the quality and efficiency of clinical care and to help the nation overcome the fragmented nature of its health-care system (Burke, 2010).

The adoption of interoperable EHR systems could produce efficiency and safety savings of between $142 billion and $371 billion (Hillestad et al., 2005). In 2011 Jha et al. studied their adoption in US hospitals and assessed their readiness for Meaningful Use. The researchers in that study used data from an American Hospital Association

survey conducted in 2010 to measure the percentages of applicable hospitals that have adopted basic and comprehensive EHRs. Of the 2902 hospitals reviewed, more than 15 percent had adopted at least a “basic” EHR, representing nearly 75 percent growth since 2008 (Jha et al., 2011). Recent numbers released by CMS on healthit.gov suggest the EHR adoption rates continue to rise as the Meaningful Use incentives take effect. Adoption of EHR systems by non-federal acute care hospitals has steadily increased since HITECH. In 2013, nearly 59 percent non-federal acute care hospitals had adopted at least a basic EHR system with clinician notes. This represents a 34 percent increase from the previous year and a more than five-fold increase in EHR adoption since 2008. In addition, in 2013 a vast majority of acute care hospitals (93 percent) possessed EHR technology certified as meeting federal requirements for Meaningful Use, this is a 29 percent increase from 2011. Hospital adoption of a Basic EHR without clinician notes has declined marginally, while the systems with more advanced functionality have increased significantly (Charles et al., 2014).

In a 2014 study, Diana et al. studied the factors identified with hospitals achieving Meaningful Use criteria, using data from the 2011 American Hospital Association Annual Survey, including the Information Technology Supplement, the Centers for Medicare & Medicaid Services report of hospitals receiving meaningful use payments, and the Health Resources and Services Administration's Area Resource File. They found that 38 percent of eligible hospitals achieved Meaningful Use incentive thresholds by the end of 2012. The study identified characteristics associated with organizations that received incentive payments for having EHR in place in 2010 as a larger number of beds, a single health information technology vendor, Joint Commission accreditation, for-profit

status, Medicare share of inpatient days in the middle two quartiles, eligibility for Medicaid incentives, and a location in the Middle Atlantic or South Atlantic census region. The characteristics associated with not receiving incentive payments were membership in a hospital system and being located in the Mountain or Pacific census region. Diana et al. (2014) concluded that little evidence suggests that the HITECH incentive program has enticed hospitals without an EHR system to adopt Meaningful Use criteria. Policy makers should consider modifying the incentive program to accelerate the adoption of and meaningful use in hospitals without EHRs.

Between 2008 and 2013, the number of hospitals with a Meaningful Use compliant EHR doubled. There was a dramatic increase in the number of hospitals that deployed CPOE and advanced clinical decision support (Gur-Arie, 2013).

Summary

A number of studies have shown that patient safety is of great concern to the entire healthcare community, especially to patients. Covell & Ritchie (2009) concluded that even though healthcare providers have ethical and professional obligations to disclose adverse events, medication errors continue to be underreported. Consequently, little is known about the types of medication errors that are not reported. Shojania et al. (2001) found that many patient safety practices drawn primarily from nonmedical fields (e.g., use of simulators, bar coding, computerized physician order entry, crew resource management) deserve additional research to illuminate their value in the health care environment. Varkey & Bisping (2007) found that interventions resulted in a decrease in prescription medication errors significantly.

In our review, healthcare information technology is shown to play a significant role in the delivery of care, and a number of studies show a positive correlation between healthcare information technology and improvement in the quality of care. Spina et al. found that 90 percent of all providers felt that the VA's electronic prescribing system, including its order check, improved prescribing safety to some degree. CPOE with CDS were shown to improve patient safety, according to Kurshal et al. (2006). More evidence was offered by Dexter et al. that CPOE can also improve compliance with provider guidelines, as well as the efficiency of hospital workflows. In their 2004 study, Handler et al. suggest that CPOE and decision support systems (DSS) can reduce certain types of errors, and Birkmeyer (2004) also concluded that CPOEs have a positive correlation to the reduction of medication errors.

Studies also revealed that although the level of EHR adoption has increased, the true impact of Meaningful Use is still to be determined. In 2010 Jha et al. found that EHR adoption had increased to about 75 percent since 2008. Charles et al. (2014) show that the number of EHRs with less advance features has declined marginally, while the number of systems with more advance functionality has increased significantly. In a related study, Diana et al. (2014) found that 38 percent of eligible hospitals had achieved Meaningful Use incentive thresholds by the end of 2012. A number of studies were reviewed that point to an increase in EHR adoption, but few or none showing the true impact of the Meaningful Use incentives. That may come in time as systems mature and data is collected on these newly implemented features.

Overall, the review of the available literature did shine a light on the importance of patient safety practices and shows the impact of various parts of an EHR on patient

safety and quality, but nothing significant relating to how advanced EHRs are impacting medication errors. Our study attempts to fill this void and add to the knowledge base in the area of patient safety.

CHAPTER 3

METHODOLOGY

Study Objective

There had been little research on the relationship between advanced EHRs and medication errors rates in inpatient settings, using the HIMSS Analytics participating hospitals as the sample population. Various studies had attempted to show the value of various aspects of technology on patient care, yet no comprehensive research had been conducted to evaluate the relationship between advanced EHRs and medication errors in hospitals. This study is important because the EHR adoption rate has increased significantly over the past few years, and to know the relationship between advance EHRs and medication error rates can contribute to development of strategies that can significantly affect quality of care. In this study, we analyzed HIMSS Analytics, AHA, and NIS data to evaluate the impact of using advanced EHRs on adverse events in healthcare, specifically comparing medication errors rates between hospitals using advanced EHRs (Stage 3) and hospitals not using an advanced EHR. For the purposes of this study, an advanced EHR necessarily included Computerized Provider Order Entry (CPOE) and Clinical Decision Support (CDS), which corresponds to Stage 3 EHR adoption.

Study Design

We conducted a retrospective, cross sectional patient-level study using the data from HIMSS Analytics for each hospital's advanced EHR adoption scores, AHA

datasets, and the NIS data for the medication error rates. We analyzed the data to determine to what extent medication errors are affected by advance EHRs. We identified the independent variable as advanced EHR usage, and its effects on medication error rates were measured.

Specification of Variables

In this study, the independent variable was advanced (Stage 3) EHR usage. The EHR usage level was classified into four stages based on various components of an EHR reported to be in use at the time of reporting. These measures were grouped into categories to measure the level EHR functionality of each hospital in its EHR journey (see Table 1). This was appropriate for our study in that it allowed us to measure the effects on medication error rates for each hospital as the hospital adopts additional components of an EHR. The categories we used are Stage 0 (no EHR applications installed), Stage 1 (EHR with ancillary services including a clinical data repository, pharmacy, laboratory, and radiology information systems), Stage 2 (Stage 1 plus EHR with nursing workflow including electronic nursing documentation and medication administration records), and Stage 3 (EHR with Stage 1 and 2 components, plus CPOE and clinical decision support). A hospital with Stage 3 EHR reported successful implementation all of all Stage 1 and Stage 2 applications plus CPOE and CDS. Teufel et al. (2012) point out that many of the functions present in advanced Stage 3 would be considered minimal functions required to meet Meaningful Use objectives. Since Stage 3 consists of more advanced automated features, we expected Stage 3 hospitals to possess enhance capabilities to handle the demands of providing high quality care, which in turn affects the patient safety capabilities of those hospitals.

The dependent variable in this study was the number of medication errors found at participating hospitals. The results were compared to a control group of hospitals without advanced EHRs that were in Stages 0, 1, and 2 of EHR classification. The control group for non-advanced EHR represented EHRs without CPOE of CDS. We tested whether the experimental treatment/condition (advanced EHR) is associated with fewer medication errors, and whether there is sufficient evidence to support the claim that it is. We controlled for several hospital level variables: teaching status, urban location, bed count, and geographical region. Given that the patient was the unit of analysis, we also controlled for patient level variables: patient age, gender, race, private insurance coverage, Medicare and Medicaid coverage, and whether the patient arrived as a transfer. We also controlled for potential selection bias of advanced EHR use in hospitals and potential differences in patient demographics, severity of errors, and hospital case mix through the use of a propensity score stratification model. To calculate the propensity score, a logistic regression analysis was performed to estimate the likelihood of each patient being seen in a hospital with an advanced EHR (Table 5). Once calculated, the propensity score variable was added to the multivariate model to control for potential selection bias. Use of a propensity score approach can remove upward of 95% of bias from estimates (Teufel et al., 2012).

Data Collection

We used secondary data from the HIMSS Analytics 2009 database for hospitals in combination with The Healthcare Cost and Utilization Project's (HCUP) National Inpatient Sample (NIS) 2009 data for patient identifiers for medication errors and AHA datasets. The HIMSS Analytics data were combined with demographic data from NIS to

measure the impact of advanced EHR use and medication error rates. NIS is a family of health care databases and related software products developed through a federal-state-industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ). NIS databases bring together the data collection efforts of state data organizations, hospital associations, private data organizations, and the federal government to create a national information resource of encounter-level health care data, the National Inpatient Sample (NIS). NIS includes the largest collection of longitudinal hospital care data in the United States, with all-payer, encounter-level information beginning in 1988. These databases enable research on a broad range of health policy issues, including cost and quality of health services, medical practice patterns, access to health care programs, and outcomes of treatments at the national, state, and local market levels (AHRQ.gov). The AHA database is based on an annual survey of US hospitals that collects data about hospital characteristics and was used for control variables. The International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes, assigned to virtually all inpatient discharges, provides a readily available surveillance system capable of detecting an ADE (Table 2). The most frequently assigned ICD-9-CM codes are diagnosis codes, external cause of injury codes (E-codes), and procedure codes. In the case of an adverse drug event (ADE), a diagnosis code is used to indicate the patient's general diagnosis (e.g., 693.0, dermatitis due to drugs and medicines taken internally), while the E-code indicates the drug class thought to be responsible for these symptoms (e.g., E933.1, antineoplastic and immunosuppressive drugs causing adverse effects in therapeutic use) (see Table 2).

To determine the medication error rates, we employed the model used previously by Hougland et al. in their 2006 study. They conducted a structured chart review and abstraction to identify all Adverse Events and whether a flagged ICD-9-CM code represented an Adverse Event. Adverse Event codes were grouped into six categories to facilitate analysis: adverse drug events, surgical adverse events, misadventures, infections, device events, and other adverse events. Our study focused on the Adverse Drug Events (ADE) category to measure medication errors. Hougland et al. identified 416 ICD-9-CM codes representing ADEs (flagged ADE codes), which are represented in Table 2. The Hougland study concluded that flagged ADE codes have a positive predictive value of 25% for inpatient ADEs, and even though the flagged ADE codes model is imperfect, it does provide an immediately available ADE surveillance system.

For the purposes of identifying medication errors, we measured ADE flagged codes associated with clinical side effects, poisoning and adverse effects (see Table 2). The poisoning codes for medication errors are used relatively infrequently. However, the poisoning codes were much more likely to detect ADEs causing admission than those ADEs that occurred in the hospital. Adverse effects codes are used more commonly than the poisoning codes (Hougland et al., 2008).

Data Analysis

The number of medication errors was determined for each admission by adding the number of ICD-9 to the number of E-codes corresponding to adverse drug effects (as specified in previous studies) for each patient case. (Hougland et al., 2006) Medication errors were categorized as clinical side effects, poisonings, and other adverse effects due to various agents according to methods outlined by Hougland (2006).

Overall means (continuous variables) and proportions (categorical variables) were computed. Unadjusted analyses of patient and hospital-level characteristics were assessed by advance EHR status using t-tests (continuous variables) and chi-squared tests (categorical variables). Among those with at least one medication error, the types of errors were compared descriptively by age, race, insurance, hospital's number of beds, and hospital region

The generalized linear models predicting the number medication errors and the probability of an admission originating from hospital with an advanced electronic health records (EHRs) (i.e. propensity model) were both controlled for the following patient level variables: patient age, gender, race, All Patient Diagnosis Related Groups (APDRGs) mortality and severity, insurance type (Medicaid, Medicare, private, other), neonatal or maternal status, Diagnosis Related Group (DRG) case mix group, and whether the patient arrived as a transfer. The following hospital-level variables were also controlled for in each model: teaching status, hospital location (urban vs. rural), hospital's number of beds, and geographical region. Models were also weighted by hospital.

A generalized linear model (binomial or logistic regression) was used to assess whether the proportion of patient cases reporting at least one medication error differs from hospitals with and without advanced EHRs. Generalized linear modeling was used assess whether the number of medication errors differs between hospital with and without advanced EHRs. Because the distribution of the number of medication errors contained high prevalence of zeros, a zero-inflated Poisson model (rather than the usual Poisson model) was used to model the total number of medication errors (see Table 4). Dependent

variables following a Poisson distribution are expected to have a mean equal to the variance. In cases of excessive zero counts, this condition is not satisfied, and over-dispersion results. Over-dispersion can lead to an overestimate of standard errors, which affects the ability to determine statistical significance of covariates within the model. Furthermore, the underlying distribution is often a mixture of distributions including both a distribution predicting zeros (binomial) and a distribution predicting counts (Poisson). It has been demonstrated that the use of zero-inflated Poisson models can correct the problem of over-dispersion (Lambert, 1992).

Two methods were used to control for selection bias. First, potential selection bias of advanced EHR use in hospitals and Use of a propensity score approach has been shown to remove upward of 95 percent of bias from estimates. (Tuefel, 2012). Potential differences in patient demographics, case severity, and hospital case mix were controlled by using propensity score stratification. The propensity score was generated by modeling advanced EHR use by fitting a logistic regression model and estimating the probability of advanced EHR for each patient case. These probabilities were stratified into quintiles, and the stratified variable was added to the final model associating advanced EHR with the outcomes of interest. Data were analyzed using SAS version 9.3, and the model was run using the GENMOD procedure (SAS Institute Inc., 2002-2010) (see Table 6).

Second, potential selection bias due to case mix, patient and hospital characteristics were examined using propensity score matching techniques. A five percent random sample of the data was developed using propensity score matching based on the nearest neighbor-matching greedy algorithm approach. The sample was limited to

30,695 randomly selected observations from each group (hospitals with and without advanced EHR.)

CHAPTER IV: FINDINGS

A 20 percent simple random sample of the combined 2009 NIS and HIMSS datasets was utilized for this analysis. A total of 1,032,905 patient cases were selected. A total of 301,289 (29.2%) patient cases originated from hospitals with an advanced EHR. A total of 550 hospitals were included in the analysis, with 104 (18.9%) reporting use of advanced EHR. The total number of medication errors per patient case ranged 0-11. The total number of admissions with at least one medication error was 67,724 (6.6%), and the average number of medication errors per patient case was 0.08 (SD = 0.35) overall, which reflects the large number of patient cases reporting zero medication errors. The average number of medication errors among patient cases with at least one medication error was 1.27 (SD = 0.61), with an average of 1.27 (SD = 0.59) among admissions with advanced EHR, and 1.27 (SD = 0.62) among those without advanced EHR, $p < 0.0001$.

Table 3 displays unadjusted differences in patient and hospital characteristics. All differences were statistically significant. The majority of covariate differences were small. Compared to patient cases from hospitals without advanced EHR, those with advanced EHR included a lower proportion of medication errors (6.7% vs. 6.3%, $p < 0.0001$), were slightly younger in age, had a higher proportion of teaching hospitals and hospitals in urban locations. Other differences are displayed in Table 3.

Additional unadjusted descriptive analyses of the subgroup of patient cases with medication errors indicated that the majority of reported medication errors were adverse

drug effects, while the least reported was poisonings as categorized by Hougland et al. in their 2006 study. Adverse drug effects were highest among the oldest age group; while poisonings were highest among the 18-44 year olds (see Table 2). The proportion of patient cases reporting clinical side effects was similar among the adult age groups. Among all patient cases with medication errors, White was the predominant race/ethnicity represented, and the most prevalent payer/insurance was Medicare, reflecting the demographic distribution of the patient population. Similarly, the majority of medication errors were among the larger sized hospitals. The largest proportion of patient cases reporting medication errors were from the South (31.6%), however, the rates by geographical region were similar for each medication error category (see Table 3).

Results of the zero-inflated Poisson models revealed that advanced EHR was positively associated with medication error, $\beta = 0.0455$ ($p < 0.001$), indicating that admissions with advanced EHRs were five percent more likely to have zero medication errors (OR = 1.047, 95% CI = 1.028-1.066) (see Table 4). No statistically significant association between the number of advanced EHRs and medication errors was detected from the Poisson portion of the regression model, $\beta = 0.0095$ ($p = 0.2058$) (see Table 5). Variables associated with both presence of medication error and an increased number of medication errors, included gender, race, risk severity, neonatal or maternal admission status, teaching hospital designation, urban location, geographical region of hospital, case mix, and propensity strata. Age was associated with a greater number of medication errors than were risk mortality, hospital's number of beds, and insurance, which were each associated with at least one medication error.

Although the two-part model (zero-inflated Poisson) used to assess the association between advanced EHR and number of medication errors included a model for assessing the presence or absence of medication error, a second model was used to assess the second objective (to determine whether the proportion of medication errors differs in hospitals that do and do not use advanced EHRs). The remaining analyses focused on the logistic regression model because (1) statistically significant association between the presence of medication error and advanced EHR use were detected; (2) no statistically significant association between total number of medication errors and advanced EHR use were detected; and (3) the high proportion of zero medication errors per patient case considerably lowers the overall average below 1, making the mean values uninformative, indicating that the more valuable indicator is presence of medication error alone. Controlling for propensity strata, patient and hospital characteristics in the multivariable logistic regression model, the proportion of medication errors among hospitals without advanced EHRs was 4.0%, while the proportion of medication errors among hospitals with advanced EHRs was 3.9% ($p < 0.0001$) (see Table 4). Results from both the zero-inflated Poisson and the logistic regression models were controlled for propensity strata (see Table 6).

Use of propensity score matching in the sensitivity analyses reduced the heterogeneity in the advanced EHR and non-advanced EHR groups as evidenced by the decrease in absolute standardized differences between covariates in the original dataset and the matched sample (see Figure 1). Using the propensity matched sample, a slightly higher proportion of medication errors was detected among the advanced EHR group however, this association was no longer statistically significant (3.7% vs. 3.6%, p =

0.3958). This indicates that the small statistically significant difference revealed in prior analyses may have been due to selection bias.

Discussion

The most important finding in this study is that there was only a small difference in the assumed direction to begin with, but it remained when using the propensity score stratification although the association was no longer statistically significant when using the matched sample. This is likely due first to the small prevalence of medication errors overall and second, to the early stages implementation of advanced EHRs, as our data set is from 2009.

Initial analyses provided weak evidence that advanced EHR could potentially reduce medication error; however, sensitivity analyses indicated that this small difference may have been due to bias. Nearly identical estimates for the average number of medication errors and proportions of medication error in each group in dataset of this large size further indicate no difference in medication error among patient cases with and without advanced EHR. Additional analyses of the subgroup of patients with at least one medical error did not reveal differences in the average number medication errors among advanced and non-advanced EHR hospitals.

While this analysis was strengthened by its use of sensitivity analyses to control selection bias, there are limitations. First, the data are cross-sectional, and at best only provide weak evidence of any association between hospitals with and without advanced EHR and medication error with any implication of a cause and effect relationship. Second, data were collected in 2009, which represented a time of EHR uptake among

hospitals. Thus, it is possible that even hospitals reporting advanced EHR may not have fully or properly implemented all elements that could have had an effect on medication errors. This uncaptured heterogeneity in advanced EHR hospitals could have weakened the ability to detect differences in groups. Third, medication errors were identified using ICD-9 codes consistent with medication errors and may not as sufficiently capture all medication errors as more thorough review of records. Studies reporting more medication errors at baseline have been associated with intervention study findings of greater reductions in medication errors (Nuckols et al., 2014). Fourth, comparisons between advanced EHR and all non-EHR, rather than solely focusing on hospitals without any EHR could have produced greater differences. However, such an approach would not have adequately measured specific differences in the stage of EHR, which was the focus of this study. Fifth, some studies have indicated that the mere presence or absence of an EHR may not affect medication error or adverse effects in general with other characteristics that are key to implementation such as physician buy-in and ease of use (Encinosa & Bae, 2013). Finally, this study did not focus on any particular patient group, and it is possible that differences may be observed among subgroups that are not detectable across all patient populations.

Although the result of little to no difference between rates of medication error in advanced vs. non-advanced EHR hospitals differs from results of other studies, descriptive analyses of characteristics of medication errors in general reflect that of previous reports of healthcare utilization data. For example, a 2004 report of adverse events found an overall prevalence of adverse drug events of about 3.1 (somewhat similar

to the adjusted estimates of 4.0 and 3.9 reported in this study). Additionally, the distributions of medication error categories by age were similar.

Additionally, the data used for our study are from 2009 and before the meaningful use incentives took effect, which may also partially explain our results. The investment from both the public and private sector increased significantly after 2009 to enhance the functionality of EHRs. Consequently, the current data may tell a different story as, in addition, these same hospitals also have more experience using EHR systems than they did six years ago.

Technology alone will not solve the problem of medication errors in healthcare; there must be comprehensive approach to the problem that includes the EHRs not reliance on the EHR to solve the problem. Jha cites hyperbole around electronic health records, along with real progress toward implementation: “But the potential is not going to be realized unless those tools are really focused on improving patient safety. The tools themselves won't automatically do it” (McCann, 2014).

Limitations

The data from HIMSS Analytics are mostly self-reported, causing some concerns with the accuracy, but not significant enough concerns to affect the validity of this study.

Some other limitations are low reporting of adverse events, complexity of EHR variability in configuration, low CPOE adoption rates and the lack of causation between advanced EHR use and medication errors. Another limitation of our study is the age of our data, which is from 2009 and is used because 2009 was the year HITECH was enacted as part of the American Reinvestment and Recovery Act (ARRA) passed by

Congress. This gives us a picture of the effects of using an advanced EHR before the Meaningful Use incentives took effect. Also, we can only show association, not causation, among our variables

A follow up study with current data is highly recommended to see how the results will differ with all the technology and process enhancements since 2009, as hospitals are now required to attest to a significant number of new advance features within an EHR plus other meaningful use measures. It's not acceptable anymore to limit CPOE or EHR use to one unit. Also, early adopters also have a lot more experience in using EHRs which should reveal much more utility across the board.

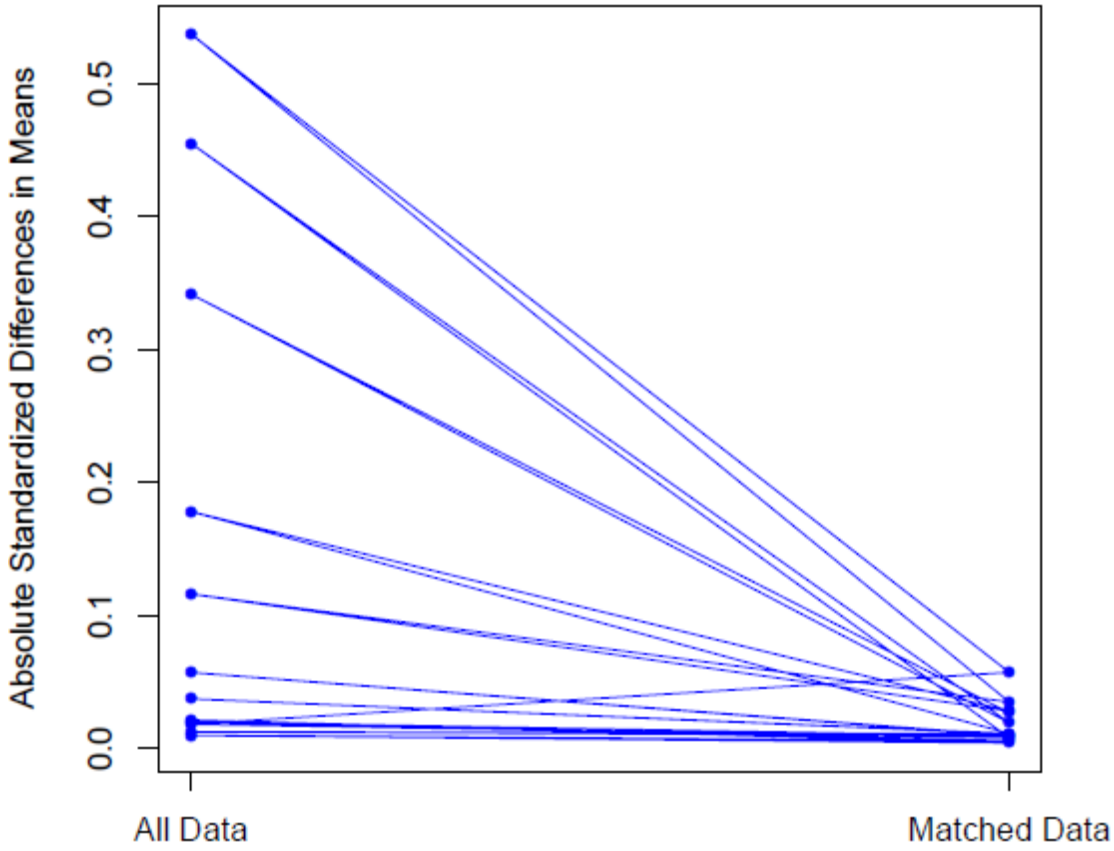
.

FIGURES AND TABLES

FIGURES

Figure 1

Standardized Mean Differences Plot



TABLES

Table 1

EHR Adoption Model

Stage	Descriptor
Stage 0	No EHR applications installed
Stage 1	EHR with ancillary services including a clinical data repository, pharmacy, laboratory, and radiology information systems
Stage 2	Stage 1 plus EHR with nursing workflow including electronic nursing documentation and medication administration records
Stage 3 (Advanced EHR)	EHR with Stage 1 and 2 components, plus CPOE and clinical decision support

(Kazley, 2014)

Table 2

International Classification of Diseases, 9th Revision, Clinical Modification Adverse Drug Events Flag Code

ADE Type	Class	ICD9 Flag Code
Clinical side effects	Drug psychoses	292.0–292.9
Clinical side effects	Dermatitis	692.3, 692.9, 693.0, 693.8, 693.9
Clinical side effects	Maternal causes of perinatal morbidity/mortality, drug reactions and intoxications specific to newborn	760.72, 760.74, 763.5, 779.4
Clinical side effects	Rash, spontaneous ecchymoses	782.1, 782.7
Poisonings	By antibiotics and other antiinfectives	960–961, E856–857
Poisonings	By hormones and synthetic substitutes	962, E858.0
Poisonings	By primarily systemic agents	963, E858.1
Poisonings	By agents primarily affecting blood constituents	964, E858.2
Poisonings	By analgesics, antipyretics, antirheumatics	965, E850
Poisonings	By anticonvulsant and anti-Parkinsonian drugs	966, E855.0
Poisonings	By sedatives and hypnotics	967, E851–852
Poisonings	By other central nervous system depressants, stimulants, anesthetics, nervous system agents	968, E855.1–855.9
Poisonings	By psychotropic agents	969, E853–854
Poisonings	By other agents	969, E853–854
Adverse effects	Of antibiotics and other antiinfectives	E930–931
Adverse effects	Of hormones and synthetic substitutes	E932
Adverse effects	Of primarily systemic agents	E933
Adverse effects	Of agents primarily affecting blood constituents	E934
Adverse effects	Of analgesics, antipyretics, antirheumatics	E935
Adverse effects	Of anticonvulsant and anti-	E936

ADE Type	Class	ICD9 Flag Code
	Parkinsonian drugs	
Adverse effects	Of sedatives and hypnotics	E937
Adverse effects	Of other central nervous system depressants, stimulants, anesthetics, nervous system agents	E938, E940–941
Adverse effects	Of psychotropic agents	E939
Adverse effects	Of agents primarily affecting the cardiovascular system	E942
Adverse effects	Of other drugs, biological, medicinal substances in therapeutic use	E943–E949

Source: Hougland et al., 2006

Table 3

Hospital and Patient Characteristics by Advanced EHR Status

	Total (n=1032905) Mean (SD) n (%)	No Advanced EHRs (n=731616) Mean (SD) n (%)	Advanced EHRs (n=301289) Mean (SD) n (%)	p-value
Age in years	48.3 (27.9)	49.4 (27.7)	45.9 (28.0)	<0.0001
Risk mortality	1.60 (0.88)	1.62 (0.88)	1.57 (0.87)	<0.0001
Risk severity	1.97 (0.91)	1.95 (0.91)	1.97 (0.91)	<0.0001
Adverse drug events	67,724 (6.6)	48,772 (6.7)	18,952 (6.3)	<0.0001
Medicaid	215,441 (20.9)	149,105 (20.4)	66,338 (22.1)	<0.0001
Medicare	380,804 (36.9)	281,521 (38.5)	99,283 (33.1)	
Private insurance	343,188 (33.3)	237,420 (32.5)	105,768 (35.2)	
Other ins/self pay/no charge	91,350 (8.9)	62,332 (8.5)	29,018 (9.7)	
Neonatal/maternal admit	235,592 (22.8)	162,799 (22.3)	72,793 (24.2)	<0.0001
Transfer into hospital	56,766 (5.5)	35,497 (4.9)	21,269 (7.1)	<0.0001
Race/Ethnicity				
White	591,032 (57.2)	433,788 (59.3)	157,244 (52.2)	<0.0001
Black	117,404 (11.4)	76,097 (10.4)	41,307 (13.7)	
Hispanic	124,379 (12.0)	90,275 (12.3)	34,104 (11.3)	
Other/missing	200,086 (12.0)	131,452 (18.0)	68,634 (22.8)	
Teaching hospital	504,828 (48.9)	310,797 (42.5)	194,031 (64.4)	<0.0001
Urban hospital	930,479 (90.1)	639,567 (87.4)	290,912 (96.6)	<0.0001
Small hospital	116,715 (11.3)	93,943 (12.8)	22,772 (7.6)	<0.0001
Medium hospital	248,545 (24.1)	170,981 (23.4)	77,564 (25.7)	
Large hospital	667,645 (64.6)	466,692 (63.8)	200,953 (66.7)	
Northeastern United States	281,526 (27.3)	166,609 (22.8)	114,917 (38.1)	<0.0001
Midwestern United States	133,327 (12.9)	72,746 (9.9)	60,581 (20.1)	
Western United States	295,064 (28.6)	22,9429 (31.4)	65,635 (21.8)	
Southern United States	322,988 (31.3)	262,832 (35.9)	60,156 (20.0)	

Table 4

Zero-Inflated Poisson Parameter Estimates

	Poisson			Binomial (Probability of zero medication errors)		
Variable	Estimate	95% CI	P	Estimate	95% CI	p
Advanced EHRs	0.0095	-0.0052, 0.0242	0.2058	0.0045	0.0273, 0.0637	<0.0001
Age	-0.0101	-0.0105, -0.0096	<0.0001	-0.0008	-0.0013, -0.0002	0.0051
Female	0.0784	0.0656, 0.0911	<0.0001	-0.0434	-0.0593, -0.0275	<0.0001
Race						
Black	-0.5211	-0.5466, -0.4957	<0.0001	-0.3960	-0.4304, -0.3617	<0.0001
Hispanic	-0.3660	-0.3930, -0.3390	<0.0001	0.0840	0.0521, 0.1160,	<0.0001
Other/unknown	-0.2649	-0.2870, -0.2427	<0.0001	-0.1527	-0.1803, -0.1250	<0.0001
White (ref)	Ref					
Risk mortality	-0.0059	-0.0164, 0.0047	0.2744	-0.1992	-0.2128, -0.1855	<0.0001
Risk severity	0.0617	0.0502, 0.0732	<0.0001	-0.4464	-0.4603, -0.4325	<0.0001
Neonatal or maternal admit	-0.6434	-0.6886, -0.5982	<0.0001	1.4943	1.4482, 1.5404	<0.0001
Teaching hospital	0.0871	0.0677, 0.1065	<0.001	0.1579	0.1336, 0.1822	<0.0001
Hospital's number of beds	-0.0049	-0.0161, 0.0062	0.3841	0.0450	0.0311, 0.0589	<0.0001
Urban vs. Rural location	0.1574	0.1272, 0.1876	<0.0001	0.1052	0.0672, 0.1432	<0.0001
Insurance						
Medicaid	0.0093	-0.0109, 0.0295	0.3669	-0.1367	-0.1610, -0.1124	<0.0001
Medicare	0.0217	0.0038, 0.0397	0.0178	0.0690	-0.0912, -0.0467	<0.0001
Other insurance/self-pay/no charge	0.0548	0.0315, 0.0780	<0.0001	-0.1392	-0.1671, -0.1112	<0.0001
Private	Ref					
Geographic Region						
Midwest	0.0999	0.0689, 0.1309	<0.001	-0.1725	-0.2114, -0.1336	<0.0001
Northeast	-0.0197	-0.0466, 0.0072	0.1515	0.0760	0.0428, 0.1093	<0.0001
South	-0.0763	-0.0942, -0.0584	<0.0001	-0.0178	-0.0400, 0.0044	0.1157
West	Ref					
Transferred into hospital	0.0399	0.0215, 0.0582	<0.0001	<0.0001	0.1199, 0.1666	<0.0001
Case Mix	-0.0138	-0.0169, -0.0107	<0.0001	<0.0001	0.0735, 0.0817	<0.0001
Propensity strata	-0.0695	-0.0826, -0.0563	<0.0001	<0.0001	-0.0623, -0.0295	<0.0001

Table 5

Logistic Regression Parameter Estimates

	Binomial (Probability of medication errors)		
Variable	Estimate	95% CI	P
Advanced EHRs	-0.0291	-0.0378, -0.0205	<0.0001
Age	-0.0077	-0.0079, -0.0075	<0.0001
Female	0.1081	0.1006, 0.1155	<0.0001
Race			
Black	-0.1545	-0.1669, -0.1422	<0.0001
Hispanic	-0.3871	0.4015, 0.3726	<0.0001
Other/unknown	-0.0992	-0.1110, -0.0874	<0.001
White (ref)	Ref		
Risk mortality	0.1368	0.1306, 0.1429	<0.0001
Risk severity	0.4214	0.4150, 0.4278	<0.0001
Neonatal or maternal admit	-1.9713	-1.9919, -.1.9506	<0.0001
Teaching hospital	-0.0494	-0.0606, -0.0382	<0.0001
Hospital's number of beds	-0.0366	-0.0428, -0.0303	<0.0001
Urban vs. Rural location	0.0590	0.0424, 0.0757	<0.0001
Insurance			
Medicaid	0.1238	0.1116, 0.1360	<0.0001
Medicare	0.0720	0.0614, 0,0826	<0.0001
Other insurance/self-pay/no charge	0.1527	0.1386, 0.1668	<0.0001
Private	Ref		
Geographic Region			
Midwest	0.3385	0.2108, 0.2462	<0.0001
Northeast	-0.0828	-0.0982, -0.0675	<0.0001
South	-0.0515	-0.0619, -0.0411	<0.0001
West	Ref		
Transferred into hospital	-0.0863	-0.0969, -0.0757	<0.0001
Case Mix	-0.0785	-0.0810, -0.0761	<0.0001
Propensity strata	-0;.0257	-0.0331, -0.0i83	<0.0001

Table 6

Base Estimate Propensity Strata and Matched Sample Proportions of Medication Errors Among Hospitals with and without Advanced EHR (Logistic Regression Model)

	Base Estimate Propensity Strata (n=1,032,905)	Base Estimate Propensity Matched Sample (n=61,390)
Advance EHR	0.039	0.037
No Advanced EHR	0.040	0.036
Difference	0.01*	-0.01

*p<0.05

Table 7

NPSF Recommendations for Achieving a Total Systems Approach and Culture of Safety

1. Ensure that leaders establish and sustain a safety culture.
2. Create centralized and coordinated oversight of patient safety.
3. Create a common set of metrics that reflect meaningful outcomes.
4. Increase funding for research in patient safety and implementation science.
5. Address safety across the entire care continuum.
6. Support the health care workforce.
7. Partner with patients and families for the safest care.
8. Ensure that technology is safe and optimized to improve patient safety.

Source: NPSF (2015)

ARTICLE MANUSCRIPT

Advanced Electronic Health Records (EHR) and Their Impact on Adverse Events and Medication Errors

Steven Goriah, DHA, PMP, CHCIO, FACHE©

Abby Kazley, PhD

Associate Professor, College of Health Professions, Medical University of South Carolina

Karen A. Wager, DBA

Professor and Associate Dean for Student Affairs, Medical University of South Carolina

Scott Stickles, DO

Radiologist, Mount Sinai Hospital of Queens

Correspondence regarding this article should be addressed to Steven Goriah, 28 Hazelton Circle, Briarcliff Manor NY 10510, 646-256-0923, sgoriah@gmail.com.

Abstract

Background

A review of the literature revealed the need for further analysis of the impact of advanced electronic health record (EHR) use on medication error rates within US hospitals.

Objective

To evaluate the effects of advanced electronic health record use on the medication error rates in an inpatient setting.

Study Design

A retrospective cross-sectional patient level analysis using the combined 2009 data from the National Inpatient Sample (NIS), HIMSS, and AHA datasets was conducted to study the relationship between advanced electronic health records use and medication error rates.

Findings

A random sample of 1,032,905 patient cases was selected. A total of 301,289 (29.2%) patient cases originated from hospitals with an advanced EHR. A total of 550 hospitals were included in the analysis, with 104 (18.9%) reporting use of advanced EHR. Compared to patient cases from hospitals without advanced EHR, those with advanced EHR had a lower proportion of medication errors (6.7% vs. 6.3%, $p < 0.0001$). The most important finding in this study is that there was only a small difference in the assumed direction to begin with, but it remained when using the propensity score stratification although the association was no longer statistically significant when using the matched sample.

Conclusions

While use of advanced EHRs has great potential for improving a variety of health and safety matters in the hospital, it is possible that its current implementation has not evolved enough to have an effect. Technology alone will not solve the problem, but it can be a part of the solution. We must establish a total systems approach to problem of patient safety where technology is part of the solution.

Keywords: CPOE: Computerized provider order entry (CPOE), clinical decision support (CDS), adverse drug events (ADE), medication error (ME), advanced electronic health record (EHR), The American Reinvestment & Recovery Act (ARRA), Meaningful Use

Advanced Electronic Health Records (EHR) and Their Impact on Medication Errors

Introduction

Patient safety has emerged as a central measure of quality in today's healthcare environment that has far-reaching impact on various aspects in the continuum of care. The practice of patient safety has been defined as those practices that reduce the risk of adverse events related to exposure to medical care across a range of diagnoses or conditions (Shojania et al., 2001). The Institute of Medicine (IOM) defines patient safety as the prevention of harm to patients (Berkowitz et al., 2012) and places it under the overarching umbrella of quality measures in healthcare (Kohn et al., 2000). Emphasis is placed on the system of care delivery that (1) prevents errors, (2) learns from the errors that do occur, and (3) is built on a culture of safety that involves health care professionals, organizations, and patients (Aspden, 2004). The Agency for Healthcare Research and Quality's (AHRQ) Patient Safety Network website expands upon the definition of prevention of harm, describing it as freedom from accidental or preventable injuries produced by medical care (AHRQ, 2007).

Background

A number of studies have shown that patient safety is of great concern to the entire healthcare community, especially to patients. Covell & Ritchie (2009) concluded that even though healthcare providers have ethical and professional obligations to disclose adverse events, medication errors continue to be underreported. Consequently, little is known about the types of medication errors that are not reported. Shojania et al. (2001) found that many patient safety practices drawn primarily from nonmedical fields

(e.g., use of simulators, bar coding, computerized physician order entry, crew resource management) deserve additional research to illuminate their value in the health care environment. Varkey & Bisping (2007) found that interventions resulted in a decrease in prescription medication errors significantly.

In our review, healthcare information technology is shown to play a significant role in the delivery of care, and a number of studies show a positive correlation between healthcare information technology and improvement in the quality of care. Spina et al. found that 90 percent of all providers felt that the VA's electronic prescribing system, including its order check, improved prescribing safety to some degree. CPOE with CDS were shown to improve patient safety, according to Kurshal et al. (2006). More evidence was offered by Dexter et al. (2001) that CPOE can also improve compliance with provider guidelines, as well as the efficiency of hospital workflows. In their 2004 study, Handler et al. suggest that CPOE and decision support systems (DSS) can reduce certain types of errors, and Birkmeyer (2004) also concluded that CPOEs have a positive correlation to the reduction of medication errors.

Studies also revealed that although the level of EHR adoption has increased, the true impact of Meaningful Use is still to be determined. In 2010 Jha et al. found that EHR adoption had increased to about 75 percent since 2008. Charles et al. (2014) show that the number of EHRs with less advance features has declined marginally, while the number of systems with more advance functionality has increased significantly. In a related study, Diana et al. (2014) found that 38 percent of eligible hospitals had achieved Meaningful Use incentive thresholds by the end of 2012. A number of studies were reviewed that point to an increase in EHR adoption, but few or none showing the true impact of the

Meaningful Use incentives. That may come in time as systems mature and data is collected on these newly implemented features.

Overall, the review of the available literature did shine a light on the importance of patient safety practices and shows the impact of various parts of an EHR on patient safety and quality, but nothing significant relating to how advanced EHRs are impacting medication errors. Our study will attempt to fill this void and add to the knowledge base in the area of patient safety. IOM conducted a landmark study in 1999 on medical errors and found that medical errors lead to the deaths of between 44,000 and 98,000 people in US hospitals each year (JHITA, 2000). The *Journal of the American Medical Association* gives a more conservative estimate and states that between 5,000 and 15,000 of those deaths were preventable (Gillespie, 2002). One type of medical error is an adverse drug event (ADE), which are a subset of those injuries associated with errors that occur during the ordering, administering, dispensing, and monitoring of drugs. ADEs increase morbidity, mortality and health care costs (Wolfstadt et al., 2008).

In addition to their impact on patient mortality, ADEs exact other significant costs. They have been estimated to result in higher costs due to additional care necessitated by the errors, lost income and household productivity, and disability of between $17 billion and $29 billion per year in hospitals nationwide (JHITA, 2000). The impact of medication errors is also felt when patients lose trust in the health care system and when both patients and health professionals experience reduced satisfaction. Patients who experience a long hospital stay or disability as a result of errors experience physical and psychological discomfort. Health professionals pay with loss of morale and frustration at not being able to provide the best care possible. Society bears the costs of

errors as well, in terms of lost worker productivity, reduced school attendance by children, and poorer population health (Kohn et al., 2000).

A number of factors contribute to medication errors. One of the most challenging but preventable factors is the decentralized and fragmented nature of the healthcare delivery system. When patients see multiple providers in different settings, none of whom have access to complete information, it becomes easier for errors to occur (Kohn et al., 2000).

Historically, most third-party purchasers of healthcare provided little financial incentive for health care organizations and providers to improve safety and quality (Kohn et al., 2000). Pay for Performance is changing the way Medicare pays for hospital care by rewarding hospitals for delivering services of higher quality and higher value. The program is an umbrella term for initiatives aimed at improving the quality, efficiency, and overall value of health care. In some Pay for Performance models, payers consider information technology critical to improving the coordination, quality, and efficiency of care. In such a measure, payers might reward organizations for the use of an EHR to order prescriptions for their patients, a process that can both lower costs and improve quality by reducing medication errors (Cromwell et al., 2011).

Many patient safety practices that are tied to information technology, such as simulators, bar coding, computerized physician order entries, and crew resource management, which have been considered as possible strategies to avoid patient safety errors and improve healthcare processes. Although not all adverse events in healthcare are preventable, IOM concluded that many could be avoided through better professional practices, more effective teamwork, and new technology (Berkowitz et al., 2012). EHRs

that use computerized physician order entry (CPOE) with clinical decision support (CDS) have been promoted as an effective strategy to prevent the development of a drug injury defined as an adverse drug event (ADE) (Wolfstadt et al., 2008). CDS is a technology that provides clinicians with real-time feedback about a wide range of diagnostic and treatment-related information as they are entering electronic orders. By running electronic rules in the background, decision support can check for a variety of potential errors such as drug interactions, patient allergies to prescribed medications, medication contraindications, and renal- and weight-based dosing. For a number of years, organizations such as the Institute of Medicine and Leapfrog have been calling for implementation of advanced EHRs, and CPOE in particular (Milstein et al., 2000).

The pace of change has greatly accelerated since the passage of the Health Information Technology for Economic and Clinical Health Act (HITECH) which is part of the American Reinvestment & Recovery Act (ARRA) of 2009. This is an effort to transform healthcare delivery through widespread adoption and use of EHR technology. Meaningful Use is an incentive program authored by the Centers for Medicare & Medicaid Services (CMS) that provides eligible hospitals and professionals with financial incentives to implement EHR systems and demonstrate “meaningful use” of certified systems.

HITECH proposes the meaningful use of interoperable EHRs throughout the health care delivery system as a critical national goal. The concept of meaningful use rests on five pillars of health outcomes policy priorities, namely: (1) improving quality, safety, efficiency, and reducing health disparities; (2) engaging patients and families in their own healthcare; (3) improving care coordination; (4) improving population and

public health; and (5) ensuring adequate privacy and security protection for personal health information (CMS.gov).

By providing incentives to individual providers for using EHR systems in specific ways, CMS has motivated a fragmented customer base to behave more like a single customer with coherent demands. In effect, CMS, as a behind-the-scenes customer, is driving standardization and the resulting economies of scale and scope in the EHR field in the same way that large industry players have been able to standardize and draw value from IT use in banking, retail merchandising, airlines, food services, and other sectors of the economy. Understanding that markets are often slow to respond to customer demand, and that EHR purchasers have limited ability to evaluate the quality of EHR vendor products prior to purchase, HITECH also created federal certification of EHR products. This certification gives a degree of assurance to providers and CMS about the quality of EHR products they purchase (HealthIT.gov, 2016).

The Meaningful Use incentive program was established with three phases: Stage 1, Data Capture and Sharing; Stage 2, Advanced Clinical Processes; and Stage 3, Improved Outcomes. Stage 1 of the Meaningful Use program focuses primarily on promoting consistency of documentation in terms of what data should be captured (content) and how it should be presented (structure). It does not address in detail how data should be recorded (vocabulary) (HealthIT.gov, 2016). Stage 1 also links documentation requirements with measurement and decision support requirements to ensure that the data being captured are more than just a description of observations, diagnoses, and treatments for future reference; clinicians now had the systems and the

motivation to document in ways that would allow EHR systems to be tools for enhanced decision-making (see Table 1).

In terms of interoperability of systems, Stage 1 focuses on promoting inter-organization electronic transactions that were already gaining acceptance in the market, such as e-prescribing, lab results delivery, and public health reporting. It also laid the foundation for new types of transactions, specifically EHR-to-EHR transactions, by requiring that systems be able to generate electronic record extracts that can be read by other systems. The ability to electronically send, receive, and incorporate such extracts from other EHR systems was left for more advanced stages.

Stage 2 Meaningful Use requires hospitals and health care providers to meet more advanced requirements to qualify for incentives during this stage, and specifies what criteria electronic health records must meet to achieve certification. Specific to Stage 2, the capability to submit electronic data about immunizations is in the core set of criteria for eligible professionals (EPs), as are the capability to submit electronic data for immunizations, reportable laboratory results, and syndromic surveillance. In addition, two new public health objectives for EPs have been added to the menu set, requiring the capability to 1) identify and report cancer cases to a cancer registry and 2) identify and report non-cancer cases to specialized registries.

Stage 2 further refines the notion of system-neutral records by taking EHR-to-EHR interoperability further and requiring not just common structures (consolidated clinical document architecture (CDA)) and common content (problems, labs, medications, etc.), but use of specific vocabularies as well, such as SNOMED CT, LOINC, and RxNORM, to enable cross-system understanding of clinical information

from one organization to another. And while Stage 1 simply requires that systems be able to generate standardized clinical documents, Stage 2 requires that they be able to transport clinical information from one system to another.

Stage 3 rules were announced in October 2015, making significant changes intended to ease the reporting burden on all providers, support health information exchange, and improve patient outcomes. One important change is a shift in focus so that health IT becomes a tool for care improvement, not an end in itself.

While each stage of Meaningful Use has sent ripples of change across the EHR landscape in terms of functions and capabilities, each stage has also engendered evolution in the very definition of an EHR. While Meaningful Use is not yet complete, it is not too early to assess how it is already shaping the field. Setting common functional requirements for EHRs and incentives for users to take advantage of those functions, the Meaningful Use program has imposed a degree of coordination on healthcare that the fragmentation of the industry has prevented up until now. Meaningful Use can go only so far, however, as it is not robust enough to change larger and deeper trends in the industry that are driving business arrangements and revenue models.

Meaningful Use has certainly been successful in creating a common floor of capability across vendors' systems, which has inalterably shaped the EHR industry. It has also had a profound impact on the widespread adoption and use of EHR systems in hospitals and physician practice. Vendors have yet to reach plug-and-play capability with EHR systems, however, and it is highly unlikely that Meaningful Use will have enough influence or enough time to instill such capability in the market.

Study Purpose/Hypothesis

There has been little research on the overall effectiveness of advanced EHRs on medication errors in an inpatient setting, using the HIMSS Analytics participating hospitals as the sample population. Various studies have attempted to show the value of various aspects of technology on patient care, but no comprehensive research had conducted to evaluate the relationship between advanced EHR use and medication errors among US hospitals. This study has sought to describe the relationship between advanced EHR use and medication errors among US hospitals participating in a survey by HIMSS, a global, cause-based, not-for-profit organization focused on better health through information technology (IT). The research hypothesis of this study was that hospitals with advanced EHRs have lower rates of medication errors compared to hospitals without advanced EHRs.

Methods

Sample and Databases

The sample size was a 20% random sample of patients in the HIMSS Analytics data 2009 that includes a broad canvassing of acute care hospitals, which are also in the NIS and AHA datasets. The patients in our sample were grouped by stage of use of EHR, a model previously used by Kazley (2014), based on individual application reported to be in use by these hospitals in our sample.

Study Design

We conducted a retrospective, cross-sectional patient level study of the data from HIMSS Analytics for each hospital's advanced EHR adoption scores, AHA datasets, and the NIS data for the medication error rates. We analyzed the data to determine to what

extent medication errors are affected by advance EHR usage. We identified the independent variable as advanced EHR usage, and its effects on medication error rates were measured.

Specification of variables. In this study, the independent variable was advanced (Stage 3) EHR usage. The EHR usage level was classified into four stages based on various components of an EHR reported to be in use at the time of reporting (see Table 1). These measures were grouped into categories to measure the level EHR functionality of each hospital in its EHR journey. This was appropriate for our study in that it allowed us to measure the effects on medication error rates for each hospital as the hospital adopts additional components of an EHR. The categories we used are Stage 0 (no EHR applications installed), Stage 1 (EHR with ancillary services including a clinical data repository, pharmacy, laboratory, and radiology information systems), Stage 2 (Stage 1 plus EHR with nursing workflow including electronic nursing documentation and medication administration records), and Stage 3 (EHR with Stage 1 and 2 components, plus CPOE and clinical decision support). A hospital with Stage 3 EHR reported successful implementation all of all Stage 1 and Stage 2 applications plus CPOE and CDS. Teufel et al. (2012) point out that many of the functions present in advanced Stage 3 would be considered minimal functions required to meet Meaningful Use Stage 1 objectives. Since Stage 3 consists of more advanced automated features, we expected Stage 3 hospitals to possess enhance capabilities to handle the demands of providing high quality care, which in turn affects the patient safety capabilities of those hospitals.

The dependent variable in this study was the number of medication errors found at participating hospitals. The results were compared to a control group of hospitals

without advanced EHRs that are in Stages 0, 1, and 2 of our EHR classification model. The control group for non-advanced EHR represented EHRs without CPOE of CDS. We tested whether the experimental treatment/condition (advanced EHR) is associated with fewer medication errors, and whether there is sufficient evidence to support the claim that it is. We controlled for several hospital level variables: teaching status, urban location, bed count, and geographical region. Given that the patient was the unit of analysis, we also controlled for patient level variables: patient age, gender, race, private insurance coverage, Medicare and Medicaid coverage, and whether the patient arrived as a transfer. We also controlled for potential selection bias of advanced EHR use in hospitals and potential differences in patient demographics, severity of errors, and hospital case mix through the use of a propensity score stratification model. To calculate the propensity score, a logistic regression analysis was performed to estimate the likelihood of each patient being seen in a hospital with an advanced EHR (see Table 5). Once calculated, the propensity score variable was added to the multivariate model to control for potential selection bias. Use of a propensity score approach can remove upward of 95% of bias from estimates (Teufel et al., 2012).

Data collection. We used secondary data from the HIMSS Analytics 2009 database for hospitals in combination with the National Inpatient Sample (NIS) 2009 data for patient identifiers for medication errors and AHA datasets. The HIMSS Analytics data were combined with demographic data from NIS to measure the impact of advanced EHR use and medication error rates. NIS is a family of health care databases and related software products developed through a federal-state-industry partnership and sponsored by the Agency for Healthcare Research and Quality (AHRQ). NIS databases bring

together the data collection efforts of state data organizations, hospital associations, private data organizations, and the federal government to create a national information resource of encounter-level health care data, the National Inpatient Sample (NIS). NIS includes the largest collection of longitudinal hospital care data in the United States, with all-payer, encounter-level information beginning in 1988. These databases enable research on a broad range of health policy issues, including cost and quality of health services, medical practice patterns, access to health care programs, and outcomes of treatments at the national, state, and local market levels (AHRQ.gov). The AHA database is based on an annual survey of US hospitals that collects data about hospital characteristics and was used for control variables.

The International Classification of Diseases, 9th Revision, Clinical Modification (ICD-9-CM) codes, assigned to virtually all inpatient discharges, provides a readily available surveillance system capable of detecting an ADE. The most frequently assigned ICD-9-CM codes are diagnosis codes, external cause of injury codes (E-codes), and procedure codes. In the case of an adverse drug event (ADE), a diagnosis code is used to indicate the patient's general diagnosis (e.g., 693.0, dermatitis due to drugs and medicines taken internally), while the E-code indicates the drug class thought to be responsible for these symptoms (e.g., E933.1, antineoplastic and immunosuppressive drugs causing adverse effects in therapeutic use) (see Table 2).

To determine the medication error rates, we employed the model used previously by Hougland et al. in their 2006 study. They conducted a structured chart review and abstraction to identify all Adverse Events and whether a flagged ICD-9-CM code represented an Adverse Event. Adverse Event codes were grouped into six categories to

facilitate analysis: adverse drug events, surgical adverse events, misadventures, infections, device events, and other adverse events. Our study focused on the Adverse Drug Events (ADE) category to measure medication errors. Hougland et al. identified 416 ICD-9-CM codes representing ADEs (flagged ADE codes) which are represented in Table 2. The Hougland study concluded that flagged ADE codes have a positive predictive value of 25% for inpatient ADEs, and even though the flagged ADE codes model is imperfect, it does provide an immediately available ADE surveillance system.

For the purposes of identifying medication errors, we measured ADE flagged codes associated with clinical side effects, poisoning, and adverse effects (see Table 2). The poisoning codes for medication errors are used relatively infrequently; however, the poisoning codes were much more likely to detect ADEs causing admission than those ADEs that occurred in the hospital. Adverse effects codes are used more commonly than the poisoning codes, which are the adverse effect codes that denote adverse drug reactions (Hougland et al., 2008).

Data Analysis

The number of medication errors was determined for each admission by adding the number of ICD-9 and the number of E-codes corresponding to adverse drug effects (as specified in previous studies) for each patient case. (Hougland et al., 2006) Medication errors were categorized as clinical side effects, poisonings, and other adverse effects due to various agents according to methods outlined by Hougland (2006).

Overall means (continuous variables) and proportions (categorical variables) were computed. Unadjusted analyses of patient and hospital-level characteristics were assessed by advance EHR status using t-tests (continuous variables) and chi-squared tests

(categorical variables). Among those with at least one medication error, the types of errors were compared descriptively by age, race, insurance, hospital's number of beds, and hospital region.

The generalized linear models predicting the number of medication errors and the probability of an admission originating from hospital with an advanced electronic health records (EHRs) (i.e. propensity model) were both controlled for the following patient level variables: patient age, gender, race, All Patient Diagnosis Related Groups (APDRGs) mortality and severity, insurance type (Medicaid, Medicare, private, other), neonatal or maternal status, Diagnosis Related Group (DRG) case mix group, and whether the patient arrived as a transfer. The following hospital-level variables were also controlled for in each model: teaching status, hospital location (urban vs. rural), hospital's number of beds, and geographical region. Models were also weighted by hospital.

A generalized linear model (binomial or logistic regression) was used to assess whether the proportion of patient cases reporting at least one medication error differs from hospitals with and without advanced EHRs. Generalized linear modeling was used assess whether the number of medication errors differs between hospital with and without advanced EHRs. Because the distribution of the number of medication errors contained high prevalence of zeros, a zero-inflated Poisson model (rather than the usual Poisson model) was used to model the total number of medication errors (see Table 4). Dependent variables following a Poisson distribution are expected to have a mean equal to the variance. In cases of excessive zero counts, this condition is not satisfied, and over-dispersion results. Over-dispersion can lead to an overestimate of standard errors, which

affects the ability to determine statistical significance of covariates within the model. Furthermore, the underlying distribution is often a mixture of distributions including both a distribution predicting zeros (binomial) and a distribution predicting counts (Poisson). It has been demonstrated that the use of zero-inflated Poisson models can correct the problem of over-dispersion (Lambert, 1992).

Two methods were used to control for selection bias. First, potential selection bias of advanced EHR use in hospitals and potential differences in patient demographics, case severity, and hospital case mix were controlled by using propensity score stratification (see Table 6). The propensity score was generated by modeling advanced EHR use by fitting a logistic regression model and estimating the probability of advanced EHR for each patient case. These probabilities were stratified into quintiles, and the stratified variable was added to the final model associating advanced EHR with the outcomes of interest. Use of a propensity score approach has been shown to remove upward of 95% of bias from estimates. (Tuefel, 2012). Data were analyzed using SAS version 9.3, and the model was run using the GENMOD procedure (SAS Institute Inc., 2002-2010) (see Table 6).

Second, potential selection bias due to case mix, patient and hospital characteristics were examined using propensity score matching techniques. A five percent random sample of the data was developed using propensity score matching based on the nearest neighbor-matching greedy algorithm approach. The sample was limited to 30,695 randomly selected observations from each group (hospitals with and without advanced EHR.)

Findings

A 20 percent simple random sample of the combined 2009 NIS and NIMMSS datasets was utilized for this analysis. A total of 1,032,905 patient cases were selected. A total of 301,289 (29.2%) patient cases originated from hospitals with an advanced EHR. A total of 550 hospitals were included in the analysis, with 104 (18.9%) reporting use of advanced EHR. The total number of medication errors per patient case ranged 0-11. The total number of admissions with at least one medication error was 67,724 (6.6%), and the average number of medication errors per patient case was 0.08 (SD = 0.35) overall, which is reflective of the large number of patient cases reporting zero medication errors. The average number of medication errors among patient cases with at least one medication error was 1.27 (SD = 0.61), with an average of 1.27 (SD = 0.59) among admissions with advanced EHR, and 1.27 (SD = 0.62) among those without an advanced EHR, $p < 0.0001$.

Table 3 displays unadjusted differences in patient and hospital characteristics. All differences were statistically significant. The majority of covariate differences were small. Compared to patient cases from hospitals without advanced EHR, those with advanced EHR included a lower proportion of medication errors (6.7% vs. 6.3%, $p < 0.0001$), were slightly younger in age, had a higher proportion of teaching hospitals and hospitals in urban locations. Other differences are displayed in Table 3.

Additional unadjusted descriptive analyses of the subgroup of patient cases with medication errors indicated that the majority of reported medication errors were adverse drug effects, while the least reported was poisonings as categorized by Hougland et al. in their 2006 study. Adverse drug effects were highest among the oldest age group, while

poisonings were highest among the 18-44 year olds (see Table 2). The proportion of patient cases reporting clinical side effects was similar among the adult age groups. Among all patient cases with medication errors, White was the predominant race/ethnicity represented, and the most prevalent payer/insurance was Medicare, reflecting the distribution of the patient population. Similarly, the majority of medication errors were among the larger sized hospitals. The largest proportion of patient cases reporting medication errors were from the South (31.6%), however, the rates by geographical region were similar for each medication error category (see Table 3).

Results of the zero-inflated Poisson models revealed that advanced EHR was positively associated with medication error, $\beta = 0.0455$ ($p < 0.001$), indicating that admissions with advanced EHRs were five percent more likely to have zero medication errors (OR = 1.047, 95% CI = 1.028-1.066) (see Table 4). No statistically significant association between the number of advanced EHRs and medication errors and was detected from the Poisson portion of the regression model, $\beta = 0.0095$ ($p = 0.2058$). Variables associated with both presence of medication error and an increased number of medication errors, included gender, race, risk severity, neonatal or maternal admission status, teaching hospital designation, urban location, geographical region of hospital, case mix, and propensity strata. Age was associated with a greater number of medication errors than were risk mortality, hospital's number of beds, and insurance, which were each associated with at least one medication error.

Although the two-part model (zero-inflated Poisson) used to assess the association between advanced EHR and number of medication errors included a model for assessing the presence or absence of medication error, a second model was used to assess the

second objective (to determine whether the proportion of medication errors differs in hospitals that do and do not use advanced EHRs). The remaining analyses focused on the logistic regression model (see Table 5) because (1) statistically significant association between number of medication errors and advance EHR use were detected; (2) no statistically significant association between number of medication errors and advanced EHR use were detected; and (3) the high proportion of zero medication errors per patient case considerably lowers the overall average below 1, making the mean values uninformative, indicating that the more valuable indicator is presence of medication error alone. Controlling for propensity strata, patient and hospital characteristics in the multivariable logistic regression model, the proportion of medication errors among hospitals without advanced EHRs was 4.0%, while the proportion of medication errors among hospitals with advanced EHRs was 3.9% ($p < 0.0001$) (see Table 4). Results from both the zero-inflated Poisson and the logistic regression models were controlled for propensity strata.

Use of propensity score matching in the sensitivity analyses reduced the heterogeneity in the advanced EHR and non-advanced EHR groups as evidenced by the decrease in absolute standardized differences between covariates in the original dataset and the matched sample (Figure 1). Using the propensity matched sample, a slightly higher proportion of medication errors was detected among the advanced EHR group; however, this association was no longer statistically significant (3.7% vs. 3.6%, $p = 0.3958$). This indicates that the small statistically significant difference revealed in prior analyses may have been due to selection bias (see Table 6).

The most important finding in this study is that there was only a small difference in the assumed direction to begin with, but it remained when using the propensity score stratification even though the association was no longer statistically significant when using the matched sample. This is likely due first to the small prevalence of medication errors overall and second, to the early stages implementation of advanced EHRs, as our data set is from 2009.

Discussion

The most important finding in this study is that there was only a small difference in the assumed direction to begin with, but it remained when using the propensity score stratification although the association was no longer statistically significant when using the matched sample. This is likely due first to the small prevalence of medication errors overall and second, to the early stages implementation of advanced EHRs, as our data set is from 2009.

Initial analyses provided weak evidence that advanced EHR could potentially reduce medication error; however, sensitivity analyses indicated that this small difference may have been due to bias. Nearly identical estimates for the average number of medication errors and proportions of medication error in each group in dataset of this large size further indicate no difference in medication error among patient cases with and without advanced EHR. Additional analyses of the subgroup of patients with at least one medical error did not reveal differences in the average number medication errors among advanced and non-advanced EHR hospitals.

While this analysis was strengthened by its use of sensitivity analyses to control selection bias, there are limitations. First, the data are cross-sectional, and at best only

provide weak evidence of an association between hospitals with and without advanced EHR and medication error with any implication of a cause and effect relationship. Second, data were collected in 2009, which represented a time of EHR uptake among hospitals. Thus, it is possible that even hospitals reporting advanced EHR may not have fully or properly implemented all elements that could have had an effect on medication errors. This uncaptured heterogeneity in advanced EHR hospitals could have weakened the ability to detect differences in groups. Third, medication errors were identified using ICD-9 codes consistent with medication errors and may not as sufficiently capture all medication errors as a more thorough review of records. Studies reporting more medication errors at baseline have been associated with intervention study findings of greater reductions in medication errors (Nuckols et al., 2014). Fourth, comparisons between advanced EHR and all non-EHR, rather than solely focusing on hospitals without any EHR could have produced greater differences. However, such an approach would not have adequately measured specific differences in the stage of EHR, which was the focus of this study. Fifth, some studies have indicated that the mere presence or absence of an EHR may not affect medication error or adverse effects in general with other characteristics that are key to implementation such as physician buy-in and ease of use (Encinosa & Bae, 2013). Finally, this study did not focus on any particular patient group, and it is possible that differences may be observed among subgroups that are not detectable across all patient populations.

Although the result of little to no difference between rates of medication error in advanced vs. non-advanced EHR hospitals differs from results of other studies, descriptive analyses of characteristics of medication errors in general reflect that of

previous reports of healthcare utilization data. For example, a 2004 report of adverse events found an overall prevalence of adverse drug events of about 3.1 (somewhat similar to the adjusted estimates of 4.0 and 3.9 reported in this study). Additionally, the distributions of medication error categories by age were similar.

Additionally, the data used for our study are from 2009 and before the meaningful use incentives took effect, which may also partially explain our results. The investment from both the public and private sector increased significantly after 2009 to enhance the functionality of EHRs, so the current data may tell a different story.

Technology alone will not solve the problem of medication errors in healthcare; there must be comprehensive approach to the problem that includes the EHRs not reliance on the EHR to solve the problem. Jha cites hyperbole around electronic health records, along with real progress toward implementation: “But the potential is not going to be realized unless those tools are really focused on improving patient safety. The tools themselves won't automatically do it” (McCann, 2014)

Limitations

The data from HIMSS Analytics are mostly self-reported, causing some concerns with the accuracy, but not significant enough concerns to affect the validity of this study.

Some other limitations are low reporting of adverse events, complexity of EHR variability in configuration, low CPOE adoption rates and the lack of causation between advanced EHR use and medication errors. Another limitation of our study is the age of our data, which is from 2009 and is used because 2009 was the year HITECH was enacted as part of the American Reinvestment and Recovery Act (ARRA) passed by Congress. This gives us a picture of the effects of using an advanced EHR before the

Meaningful Use incentives took effect. Also, we can only show association, not causation, among our variables. A follow-up study with current data is highly recommended to see how the results will differ with all the technology and process enhancements since 2009, as hospitals are now required to attest to a significant number of new advance features within an EHR plus other meaningful use measures. It is not acceptable anymore to limit CPOE or EHR use to one unit. Also, early adopters also have a lot more experience in using EHRs which should reveal much more utility across the board.

Conclusion

Although technology can be used a tool as part of the solution, it is not the solution to the issues surrounding patient safety. For us to see a significant reduction in the medical errors, we must establish a total systems approach to the problem, where technology is only part of the solution. In early 2015, The National Patient Safety Foundation (NPSF) assembled a group of industry experts to assentation the current state of patient safety and they concluded in their final report that a total systems approach is needed to address the problem. In a final report entitled *Free From Harm- Accelerating Patient Safety Improvements Fifteen years after to* Err is Human, the panel provided eight recommendations for achieving total patient safety (see Table 7). The leading recommendation is to ensure that leaders establish and sustain a culture of safety; technology was included as the Number 8 recommendation. If we are to make advances in this area, this is the playbook that should be followed to establish total systems approach to patient safety.

TABLES

Table 1. EHR Adoption Model

Stage	Descriptor
Stage 0	No EHR applications installed
Stage 1	EHR with ancillary services including a clinical data repository, pharmacy, laboratory, and radiology information systems
Stage 2	Stage 1 plus EHR with nursing workflow including electronic nursing documentation and medication administration records
Stage 3 (Advanced EHR)	EHR with Stage 1 and 2 components, plus CPOE and clinical decision support

(Kazley, 2014)

Table 2. International Classification of Diseases, 9th Revision, Clinical Modification Adverse Drug Events Flag Code

ADE Type	Class	ICD9 Flag Code
Clinical side effects	Drug psychoses	292.0–292.9
Clinical side effects	Dermatitis	692.3, 692.9, 693.0, 693.8, 693.9
Clinical side effects	Maternal causes of perinatal morbidity/mortality, drug reactions and intoxications specific to newborn	760.72, 760.74, 763.5, 779.4
Clinical side effects	Rash, spontaneous ecchymoses	782.1, 782.7
Poisonings	By antibiotics and other antiinfectives	960–961, E856–857
Poisonings	By hormones and synthetic substitutes	962, E858.0
Poisonings	By primarily systemic agents	963, E858.1
Poisonings	By agents primarily affecting blood constituents	964, E858.2
Poisonings	By analgesics, antipyretics, antirheumatics	965, E850
Poisonings	By anticonvulsant and anti-Parkinsonian drugs	966, E855.0
Poisonings	By sedatives and hypnotics	967, E851–852
Poisonings	By other central nervous system depressants, stimulants, anesthetics, nervous system agents	968, E855.1–855.9
Poisonings	By psychotropic agents	969, E853–854
Poisonings	By other agents	969, E853–854
Adverse effects	Of antibiotics and other antiinfectives	E930–931
Adverse effects	Of hormones and synthetic substitutes	E932
Adverse effects	Of primarily systemic agents	E933
Adverse effects	Of agents primarily affecting blood constituents	E934
Adverse effects	Of analgesics, antipyretics, antirheumatics	E935
Adverse effects	Of anticonvulsant and anti-Parkinsonian drugs	E936
Adverse effects	Of sedatives and hypnotics	E937

ADE Type	Class	ICD9 Flag Code
Adverse effects	Of other central nervous system depressants, stimulants, anesthetics, nervous system agents	E938, E940–941
Adverse effects	Of psychotropic agents	E939
Adverse effects	Of agents primarily affecting the cardiovascular system	E942
Adverse effects	Of other drugs, biological, medicinal substances in therapeutic use	E943–E949

Source: Hougland et al., (2006)

Table 3. Hospital and Patient Characteristics by Advanced EHR Status

	Total (n = 1032905) Mean (SD) n (%)	No Advanced EHRs (n = 731616) Mean (SD) n (%)	Advanced EHRs (n = 301289) Mean (SD) n (%)	p-value
Age in years	48.3 (27.9)	49.4 (27.7)	45.9 (28.0)	<0.0001
Risk mortality	1.60 (0.88)	1.62 (0.88)	1.57 (0.87)	<0.0001
Risk severity	1.97 (0.91)	1.95 (0.91)	1.97 (0.91)	<0.0001
Adverse drug events	67,724 (6.6)	48,772 (6.7)	18,952 (6.3)	<0.0001
Medicaid	215,441 (20.9)	149,105 (20.4)	66,338 (22.1)	<0.0001
Medicare	380,804 (36.9)	281,521 (38.5)	99,283 (33.1)	
Private insurance	343,188 (33.3)	237,420 (32.5)	105,768 (35.2)	
Other ins/self pay/no charge	91,350 (8.9)	62,332 (8.5)	29,018 (9.7)	
Neonatal/maternal admit	235,592 (22.8)	162,799 (22.3)	72,793 (24.2)	<0.0001
Transfer into hospital	56,766 (5.5)	35,497 (4.9)	21,269 (7.1)	<0.0001
Race/Ethnicity				
White	591,032 (57.2)	433,788 (59.3)	157,244 (52.2)	<0.0001
Black	117,404 (11.4)	76,097 (10.4)	41,307 (13.7)	
Hispanic	124,379 (12.0)	90,275 (12.3)	34,104 (11.3)	
Other/missing	200,086 (12.0)	131,452 (18.0)	68,634 (22.8)	
Teaching hospital	504,828 (48.9)	310,797 (42.5)	194,031 (64.4)	<0.0001
Urban hospital	930,479 (90.1)	639,567 (87.4)	290,912 (96.6)	<0.0001
Small hospital	116,715 (11.3)	93,943 (12.8)	22,772 (7.6)	<0.0001
Medium hospital	248,545 (24.1)	170,981 (23.4)	77,564 (25.7)	
Large hospital	667,645 (64.6)	466,692 (63.8)	200,953 (66.7)	
Northeastern United States	281,526 (27.3)	166,609 (22.8)	114,917 (38.1)	<0.0001
Midwestern United States	133,327 (12.9)	72,746 (9.9)	60,581 (20.1)	
Western United States	295,064 (28.6)	22,9429 (31.4)	65,635 (21.8)	
Southern United States	322,988 (31.3)	262,832 (35.9)	60,156 (20.0)	

Table 4. Zero-Inflated Poisson Parameter Estimates

	Poisson			Binomial (Probability of zero medication errors)		
Variable	Estimate	95% CI	P	Estimate	95% CI	p
Advanced EHRs	0.0095	-0.0052, 0.0242	0.2058	0.0045	0.0273, 0.0637	<0.0001
Age	-0.0101	-0.0105, -0.0096	<0.0001	-0.0008	-0.0013, -0.0002	0.0051
Female	0.0784	0.0656, 0.0911	<0.0001	-0.0434	-0.0593, -0.0275	<0.0001
Race						
Black	-0.5211	-0.5466, -0.4957	<0.0001	-0.3960	-0.4304, -0.3617	<0.0001
Hispanic	-0.3660	-0.3930, -0.3390	<0.0001	0.0840	0.0521, 0.1160,	<0.0001
Other/unknown	-0.2649	-0.2870, -0.2427	<0.0001	-0.1527	-0.1803, -0.1250	<0.0001
White (ref)	Ref					
Risk mortality	-0.0059	-0.0164, 0.0047	0.2744	-0.1992	-0.2128, -0.1855	<0.0001
Risk severity	0.0617	0.0502, 0.0732	<0.0001	-0.4464	-0.4603, -0.4325	<0.0001
Neonatal or maternal admit	-0.6434	-0.6886, -0.5982	<0.0001	1.4943	1.4482, 1.5404	<0.0001
Teaching hospital	0.0871	0.0677, 0.1065	<0.001	0.1579	0.1336, 0.1822	<0.0001
Hospital's number of beds	-0.0049	-0.0161, 0.0062	0.3841	0.0450	0.0311, 0.0589	<0.0001
Urban vs. Rural location	0.1574	0.1272, 0.1876	<0.0001	0.1052	0.0672, 0.1432	<0.0001
Insurance						
Medicaid	0.0093	-0.0109, 0.0295	0.3669	-0.1367	-0.1610, -0.1124	<0.0001
Medicare	0.0217	0.0038, 0.0397	0.0178	0.0690	-0.0912, -0.0467	<0.0001
Other insurance/self-pay/no charge	0.0548	0.0315, 0.0780	<0.0001	-0.1392	-0.1671, -0.1112	<0.0001
Private	Ref					
Geographic Region						
Midwest	0.0999	0.0689, 0.1309	<0.001	-0.1725	-0.2114, -0.1336	<0.0001
Northeast	-0.0197	-0.0466, 0.0072	0.1515	0.0760	0.0428, 0.1093	<0.0001
South	-0.0763	-0.0942, -0.0584	<0.0001	-0.0178	-0.0400, 0.0044	0.1157
West	Ref					
Transferred into hospital	0.0399	0.0215, 0.0582	<0.0001	<0.0001	0.1199, 0.1666	<0.0001
Case Mix	-0.0138	-0.0169, -0.0107	<0.0001	<0.0001	0.0735, 0.0817	<0.0001
Propensity strata	-0.0695	-0.0826, -0.0563	<0.0001	<0.0001	-0.0623, -0.0295	<0.0001

Table 5. Logistic Regression Parameter Estimates

	Binomial (Probability of medication errors)		
Variable	Estimate	95% CI	P
Advanced EHRs	-0.0291	-0.0378, -0.0205	<0.0001
Age	-0.0077	-0.0079, -0.0075	<0.0001
Female	0.1081	0.1006, 0.1155	<0.0001
Race			
Black	-0.1545	-0.1669, -0.1422	<0.0001
Hispanic	-0.3871	0.4015, 0.3726	<0.0001
Other/unknown	-0.0992	-0.1110, -0.0874	<0.001
White (ref)	Ref		
Risk mortality	0.1368	0.1306, 0.1429	<0.0001
Risk severity	0.4214	0.4150, 0.4278	<0.0001
Neonatal or maternal admit	-1.9713	-1.9919, -.1.9506	<0.0001
Teaching hospital	-0.0494	-0.0606, -0.0382	<0.0001
Hospital's number of beds	-0.0366	-0.0428, -0.0303	<0.0001
Urban vs. Rural location	0.0590	0.0424, 0.0757	<0.0001
Insurance			
Medicaid	0.1238	0.1116, 0.1360	<0.0001
Medicare	0.0720	0.0614, 0,0826	<0.0001
Other insurance/self-pay/no charge	0.1527	0.1386, 0.1668	<0.0001
Private	Ref		
Geographic Region			
Midwest	0.3385	0.2108, 0.2462	<0.0001
Northeast	-0.0828	-0.0982, -0.0675	<0.0001
South	-0.0515	-0.0619, -0.0411	<0.0001
West	Ref		
Transferred into hospital	-0.0863	-0.0969, -0.0757	<0.0001
Case Mix	-0.0785	-0.0810, -0.0761	<0.0001
Propensity strata	-0;.0257	-0.0331, -0.0i83	<0.0001

Table 6. Base Estimate Propensity Strata and Matched Sample Proportions of Medication Errors Among Hospitals with and without Advanced EHR (Logistic Regression Model)

	Base Estimate Propensity Strata (n=1,032,905)	Base Estimate Propensity Matched Sample (n=61,390)
Advance EHR	0.039	0.037
No Advanced EHR	0.040	0.036
Difference	0.01*	-0.01

*p<0.05

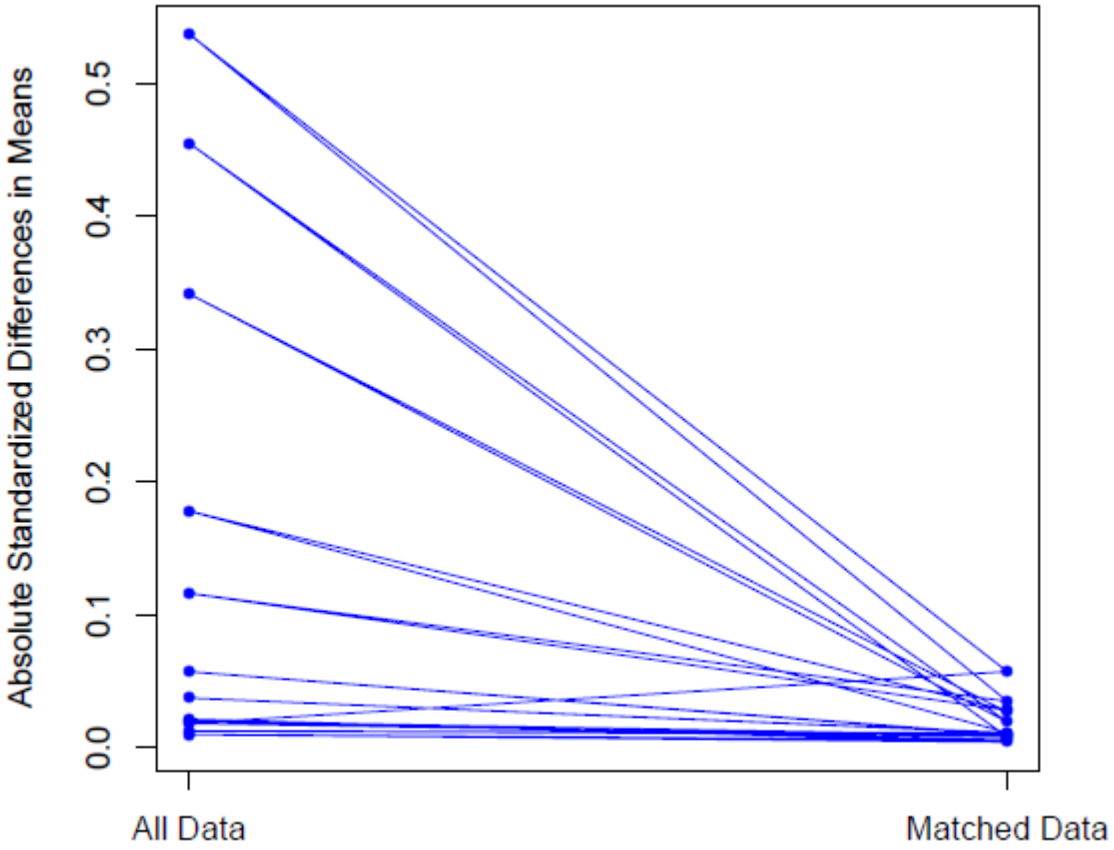
Table 7. NPSF Recommendations for Achieving a Total Systems Approach and Culture of Safety

1. Ensure that leaders establish and sustain a safety culture.
2. Create centralized and coordinated oversight of patient safety.
3. Create a common set of metrics that reflect meaningful outcomes.
4. Increase funding for research in patient safety and implementation science.
5. Address safety across the entire care continuum.
6. Support the health care workforce.
7. Partner with patients and families for the safest care.
8. Ensure that technology is safe and optimized to improve patient safety.

Source: NPSF (2015)

FIGURES

Figure 1. Standardized Mean Differences Plot



REFERENCES

Bates D. W., Teich, J. M., Lee, J., et al. (1999). The impact of computerized physician order entry on medication error prevention. *Journal American Medical Informatics Association*, 1999 Jul-Aug; 6(4): 313–21. PMCID: PMC61372. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC61372/

Berkowitz, R. E., Schreiber, R. M., & Paasche-Orlow, M. K. (2012). Team improvement and patient safety conferences culture change and slowing the revolving door between skilled nursing facility and the hospital. *Journal of Nursing Care Quality*, *27*(3): p 258–265. doi: 10.1097/NCQ.0b013e31824623a4

Birkmeyer, J.D. (2004). *The Leapfrog Group's patient safety practices, 2003: The potential benefits of universal adoption*. Washington, DC: The Leapfrog Group.

Blumenthal, D., & Tavenner, M. (2010). The "meaningful use" regulation for electronic health records. *New England Journal of Medicine*, *363*(6):501-504. Retrieved from http://www.nejm.org/doi/pdf/10.1056/NEJMp1006114

Burke, T. (2010). The health information technology provisions in the American recovery and reinvestment act of 2009: Implications for public health policy and practice. *Public Health Reports*, *125*(1):141-145. Retrieved from http://www.nejm.org/doi/pdf/10.1056/NEJMp1006114

Charles, D., Gabriel, M., & Furukawa, M. F. (2014). Adoption of electronic health record systems among U.S. non-federal acute care hospitals: 2008-2013. ONC Data Brief No. 16, May 2014. Washington DC: CMS. Retrieved from https://www.healthit.gov/sites/default/files/oncdatabrief16.pdf

Covell, C. L., & Ritchie, J. A. (2009). Nurses' responses to medication errors: Suggestions for the development of organizational strategies to improve reporting. *Journal of Nursing Care Quality 12/2009; 24(4)*:287-97. DOI:10.1097/NCQ.0b013e3181a4d506

Cromwell, J., Trisolini, M. G., Pope, G. C., Mitchell, J. B., and Greenwald, L. M., Eds. (2011). *Pay for performance in health care: Methods and approaches.* RTI Press Publication No. BK-0002-1103. Research Triangle Park, NC: RTI Press. Retrieved from https://www.rti.org/pubs/bk-0002-1103-mitchell.pdf

DeShazo, J. P., & Hoffman, M. A. (2015). A comparison of a multistate inpatient EHR database to the HCUP Nationwide Inpatient Sample. *BMC Health Services Research, 15,* 384. doi: 10.1186/s12913-015-1025-7

Dexter, P. R., Perkins, S., Overhage, J. M., Maharry, K., Kohler, R. B., & McDonald, C. J. (2001). A computerized reminder system to increase the use of preventive care for hospitalized patients. *New England Journal of Medicine 345*(13) (27 September 2001): 965–970. Retrieved from http://www.nejm.org/doi/pdf/10.1056/NEJMsa010181

Diana, M. L., Harle, C. A., Huerta, T. R., Ford, E. W., & Menachemi, N. (2014). Hospital characteristics associated with achievement of meaningful use. *Journal of Healthcare. Management, 59(4)*: 272-284. Retrieved from https://libres.uncg.edu/ir/uncg/f/E_Ford_Hospital_2014.pdf

Dow, J., Brummond, P., Ludwig, B. & Rough, S. (2012). Evaluation of the impact of computerized prescriber order entry on medication use system performance at an academic medical center. *Hospital Pharmacy, October 2012, 47(10)*: 776-782. doi: 10.1310/hpj4710-776

Encinosa, W. E., & Bae, J. (2013). Will meaningful use electronic medical records reduce hospital costs? *The American Journal of Managed Care, 19*(10 Spec No), eSP19-25.

Evans, R. S., Pestotnik, S. L., Classen, D. C., Horn, S. D., Bass, S. B., Burke J. P. (1994). Preventing adverse drug events in hospitalized patients. *Annals of Pharmacotherapy*, 1994 Apr;28(4):523-7. doi:10.1177/106002809402800417

Furukawa, M. F., Eldridge, N., Wang, Y., & Metersky, M. (2016). Electronic Health Record Adoption and Rates of In-hospital Adverse Events. *Journal of Patient Safety*, (Published Ahead of Print). doi: 10.1097/pts.0000000000000257

Gur-Arie, M. (2013). Spinning EHR adoption numbers? *HIT Consultant*. Retrieved from hitconsultant.net: http://hitconsultant.net/2013/06/20/spinning-ehr-adoption-numbers/

Gillespie G. (2002) I.T. helps steer caregivers from danger of medical errors. *Health Data Management*. May 2002. The Thompson Corporation and Health Data Management. October 8, 2003. Retrieved from http://www.healthdatamanagement.com/HDMSearchResultsDetails.cfm?DID=11760

Handler J., Feied, C., Coonan, K., Vozenilek, J., Gillam, M., Peacock, P., Jr., Sinert, R., & Smith, M. (2004). Computerized physician order entry and online decision support. *Academy of Emergency Medicine, November 2004, 11*(11): 1135-41. doi: 10.1197/j.aem.2004.08.007.

HealthIT.gov (2016) Meaningful Use regulations. https://www.healthit.gov/policy-researchers-implementers/meaningful-use-regulations (accessed March 2016)

Hillestad R., Bigelow J., Bower A., et al. (2005) Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Affairs, 24*:1103-1117.

Hougland, P., Xu, W., Pickard, S., Masheter, C., & Williams, S. D. (2006). Performance of International Classification of Diseases, 9th Revision, clinical modification codes as an adverse drug event surveillance system. *Medical Care, 44*(7), 629-636. doi: 10.1097/01.mlr.0000215859.06051.77

Jayawardena, S. (2007). Prescription errors and the impact of computerized prescription order entry system in a community-based hospital. *American Journal of Therapeutics*, 336–340. Retrieved from http://journals.lww.com/americantherapeutics/toc/2007/07000

Jha A. K. (2010). Meaningful use of electronic health records: the road ahead. JAMA. 2010; 304(15):1709-1710. doi: 10.1001/jama.2010.1497.

Jha A. K, Burke, T., DesRoches C., Joshi, M. S., Kralovec, P. D., Eric G. Campbell, E. G., & Buntin, M. B. (2011). Progress toward meaningful use: Hospitals' adoption of electronic health records. *American Journal of Managed Care 2011,17*(12, spec No.):117-124. Retrieved from http://www.ajmc.com/journals/issue/2011/2011-12-vol17-sp/progress-toward-meaningful-use-hospitalsu2019-adoption-of-electronic-health-records#sthash.9U4CuHj7.dpuf

Joint Healthcare Information Technology Alliance (JHITA) (2000). Federal response to IOM medical errors report. September 18, 2003. Retrieved from http:www.jhita.org/mederrors.htm

Kaushal, R., Jha, A. K., Franz, C., Glaser, J., Shetty K. D., Jaggi, T. … Brigham and Women's Hospital CPOE Working Group (2006). Return on investment for a computerized physician order entry system. *Journal of the American Medical Informatics Association.* 2006 May-Jun;*13*(3):261-6. Epub 2006 Feb 24. PMID:16501178 Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/16501178

Kazley, A. S. (2014). Association of electronic health records with cost savings in a national sample. *American Journal of Managed Care, 2014; 20*(6): e183-e190. Retrieved from http://www.ajmc.com/journals/issue/2014/2014-vol20-n6/association-of-electronic-health-records-with-cost-savings-in-a-national-sample

Kohn L. T., Corrigan, J. M. & Donaldson, M. S., eds. (1999). *To err is human: building a safer health system*. Institute of Medicine, Committee on Quality of Health Care in America. Washington DC: National Academies Press. Retrieved from http://www.nap.edu/read/9728/chapter/1

Lambert, D. (1992). Zero-inflated Poisson regression, with an application to defects in manufacturing. *Technometrics, 34*(1), 1-14. doi: 10.2307/1269547

Leapfrog Group (2014). *Fact sheet: Computerized physician order entry*. Retrieved from http://www.leapfroggroup.org/media/file/FactSheet_CPOE2.pdf

McCann, M. (2014). *Deaths by medical mistakes hit records*. HealthCare IT News. Retrieved 2/11/16 from http://www.healthcareitnews.com/news/deaths-by-medical-mistakes-hit-records

Milstein A., Galvin, R. S., Delbanco, S. F., Salber, P. & Buck, C. R., Jr. (2000). Improving the safety of health care: The Leapfrog Initiative. *Effective Clinical Practice 3*(6): 313-6.

National Patient Safety Foundation (NPSF) (2015). *Free from Harm: Accelerating Patient Safety Improvement Fifteen Years after* To Err Is Human. National Patient Safety Foundation, Boston, MA; 2015. Retrieved from http://www.npsf.org/?page=freefromharm

Nuckols, T. K., Smith-Spangler, C., Morton, S. C., Asch, S. M., Patel, V. M., Anderson, L. J., … Shekelle, P. G. (2014). The effectiveness of computerized order entry at reducing preventable adverse drug events and medication errors in hospital settings: A systematic review and meta-analysis. *Systematic Reviews, 3*, 56-56. doi: 10.1186/2046-4053-3-56

SAS Institute Inc. (2011). SAS Version 9.3. Cary, NC.

Shojania, K. G., Duncan, B.W., McDonald, K. M., et al., eds. (2001) Making health care safer: A critical analysis of patient safety practices. *Evidence Report/Technology Assessment No. 43*. AHRQ Publication No. 01-E058, Rockville, MD: Agency for Healthcare Research and Quality. July 2001.

Spina, J., Glassman, P., Simon, Barbara, Lanto, A., Lee, M., Cunningham, F., & Good, C. (2011). Potential safety gaps in order entry and automated drug alerts: A nationwide survey of VA physician self-reported practices with computerized order entry. *Medical Care 49(10)*: 904-10. doi: 10.1097/MLR.0b013e318222a6f5

Teufel, R. J., Kazley, A. S., Ebeling, M.D., & Basco, W. T., Jr. (2012). Hospital electronic medical record use and cost of inpatient pediatric care. *Academy of Pediatrics, 12(5)*:429-35. doi: http://dx.doi.org/10.1016/j.acap.2012.06.004

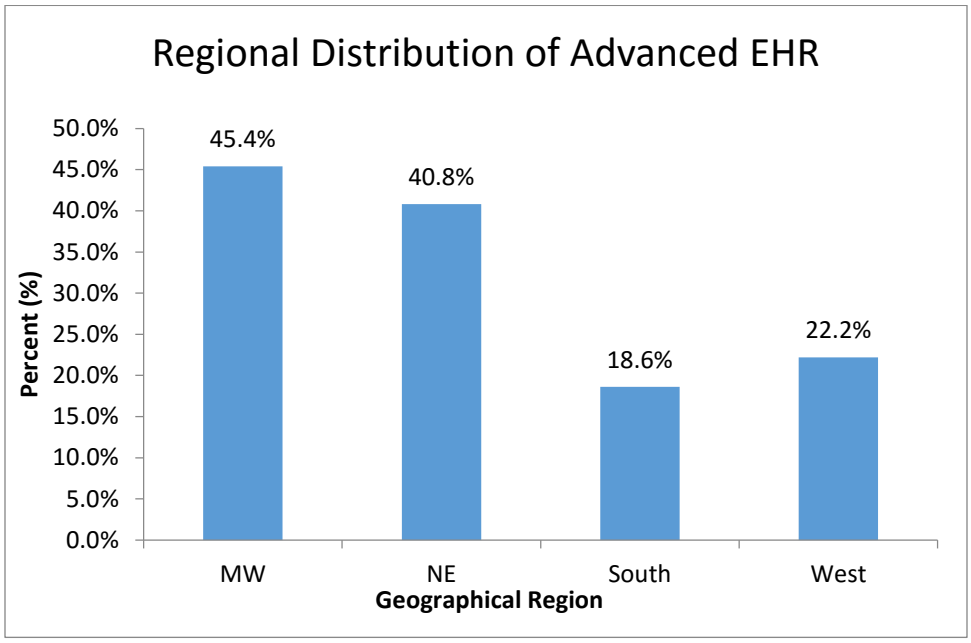
Varkey P, Cunningham J, Bisping S (2007) *Improving medication reconciliation in the outpatient setting*. The Joint Commission Journal on Quality and Patient Safety May 2007, 286-292. Retrieved from https://psnet.ahrq.gov/resources/resource/5202

Wolfstadt, J., Gurwitz, T., Field, M. L., Sunila K., Wei W., & Rochon, P. A. (2008). The effect of computerized physician order entry with clinical decision support on the rates of adverse drug events: A systematic review. *Journal of General Internal Medicine, 23(4):*451-458. doi: 10.1007/s11606-008-0504-5

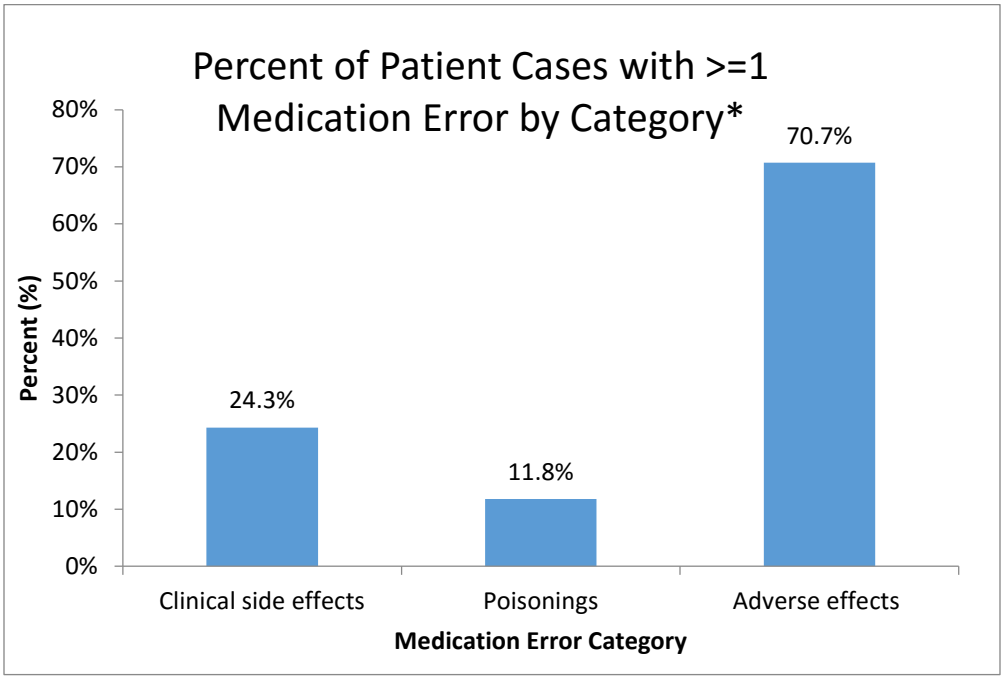
Zlabek, J. A., Wickus, J. W., & Mathiason, M. A. (2011). Early cost and safety benefits of an inpatient electronic health record. *Journal of the American Medical Informatics Association 18*:169-172. doi: http://dx.doi.org/10.1136/jamia.2010.007229

APPENDIX: ADDITIONAL DESCRIPTIVE SUMMARIES

Regional Distribution of Advanced EHRs

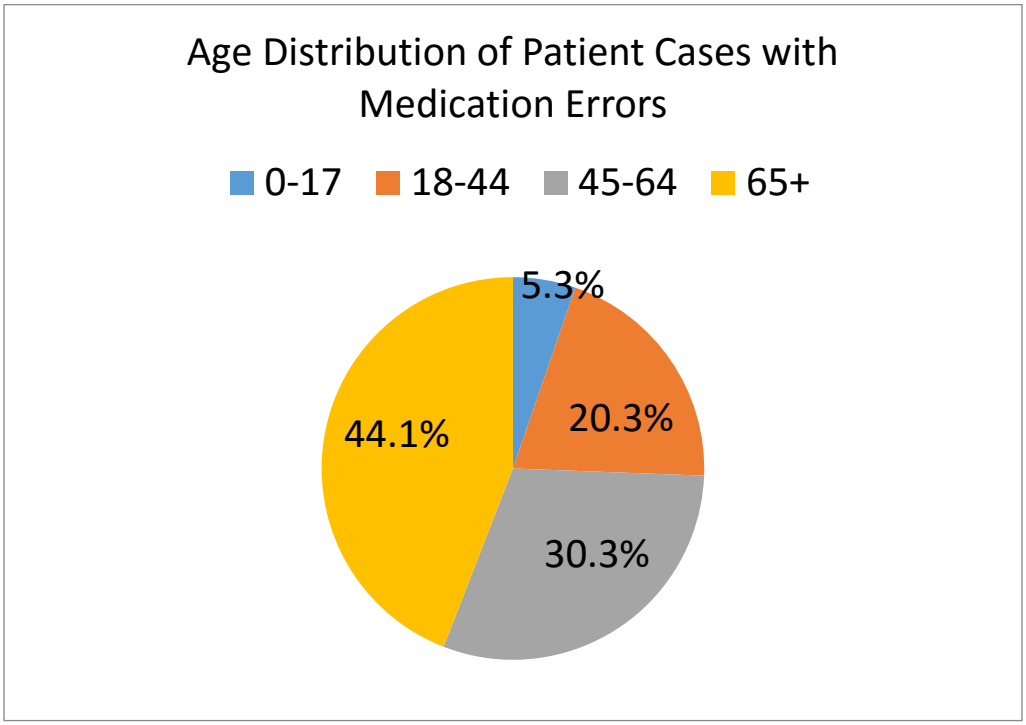


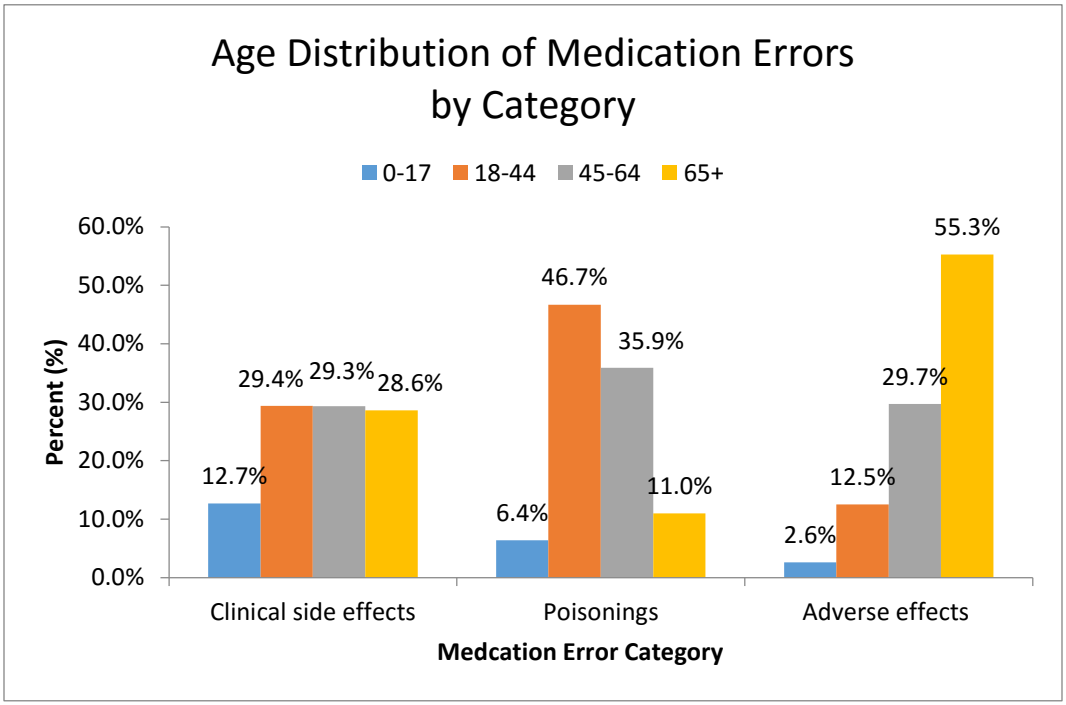
Types of Medication Errors



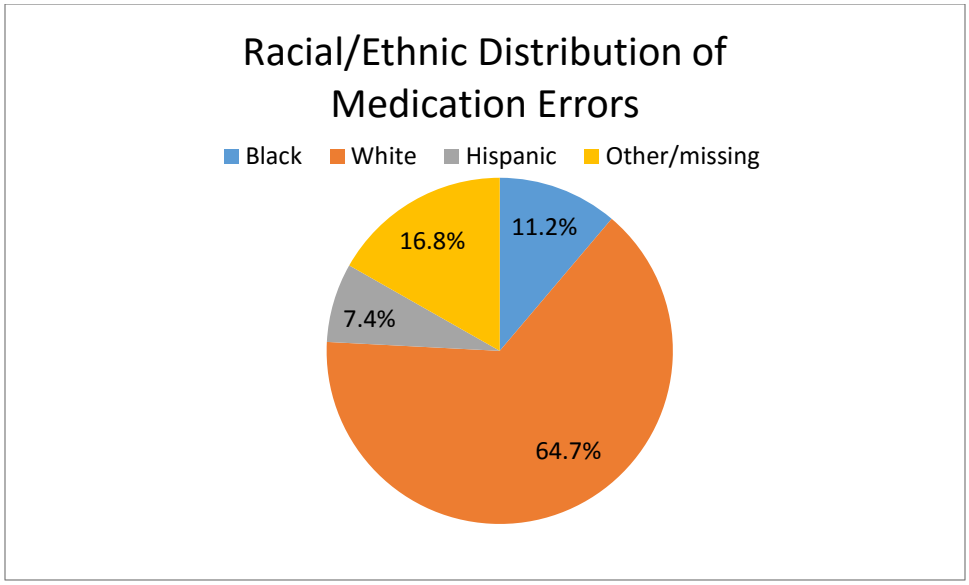
*Note: Percentage of admissions (or patient cases) with medication errors falling within each category. Categories are not mutually exclusive. Each patient case may have multiple types of medication error.

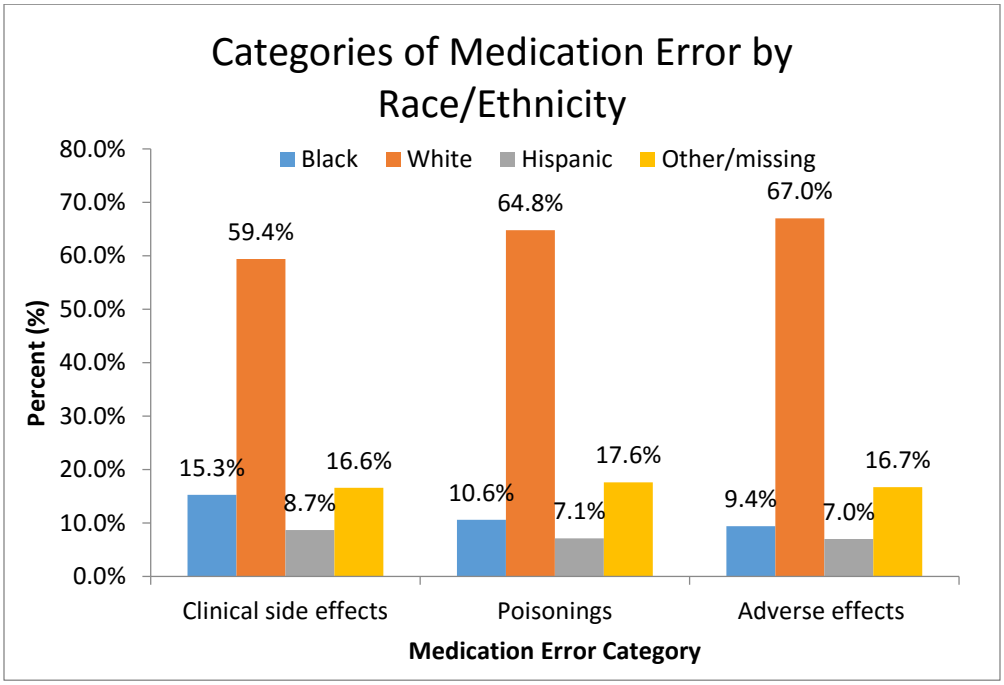
Types of Medication Errors by Age



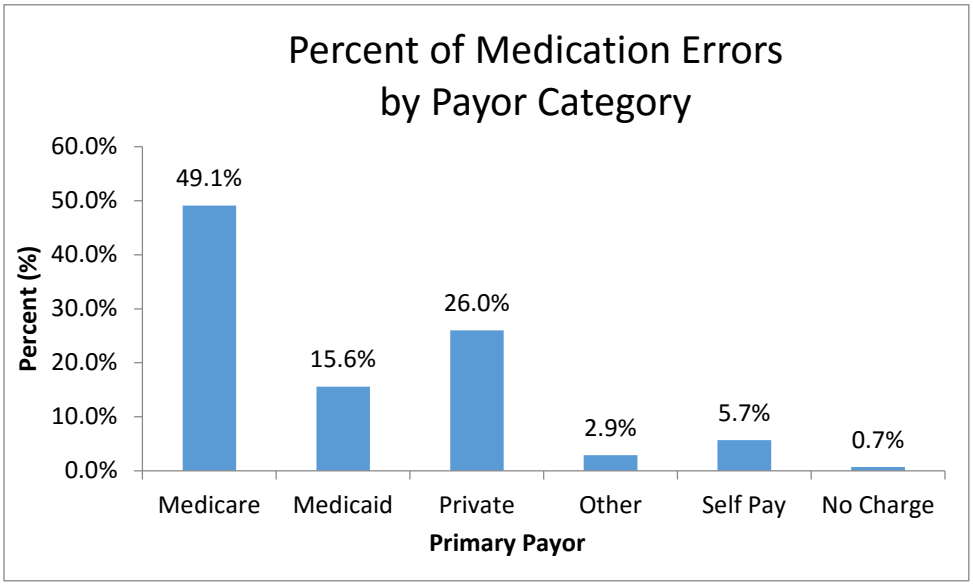


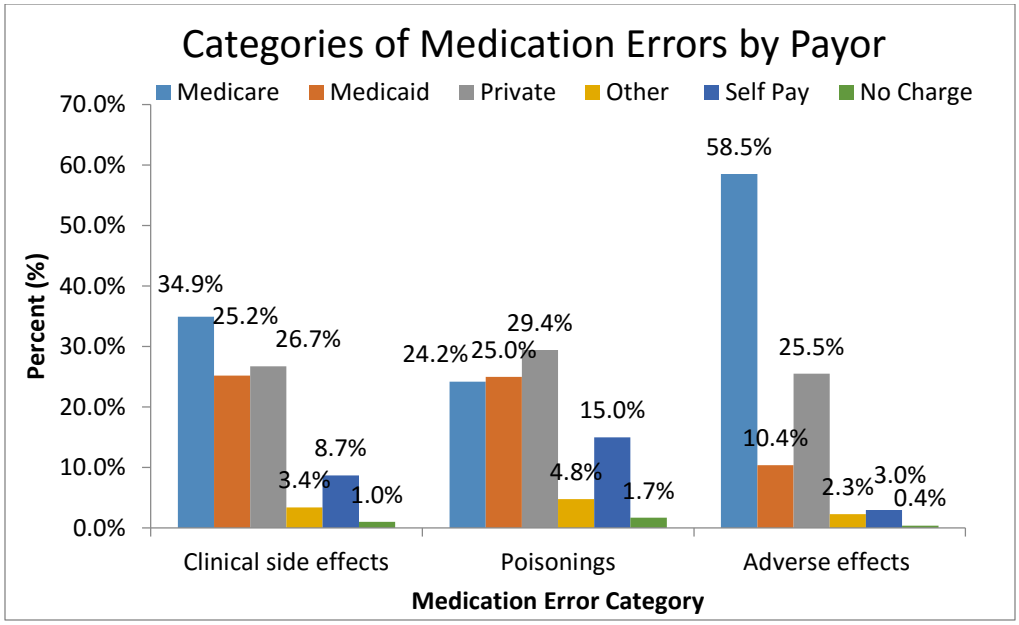
Types of Medication Errors by Race



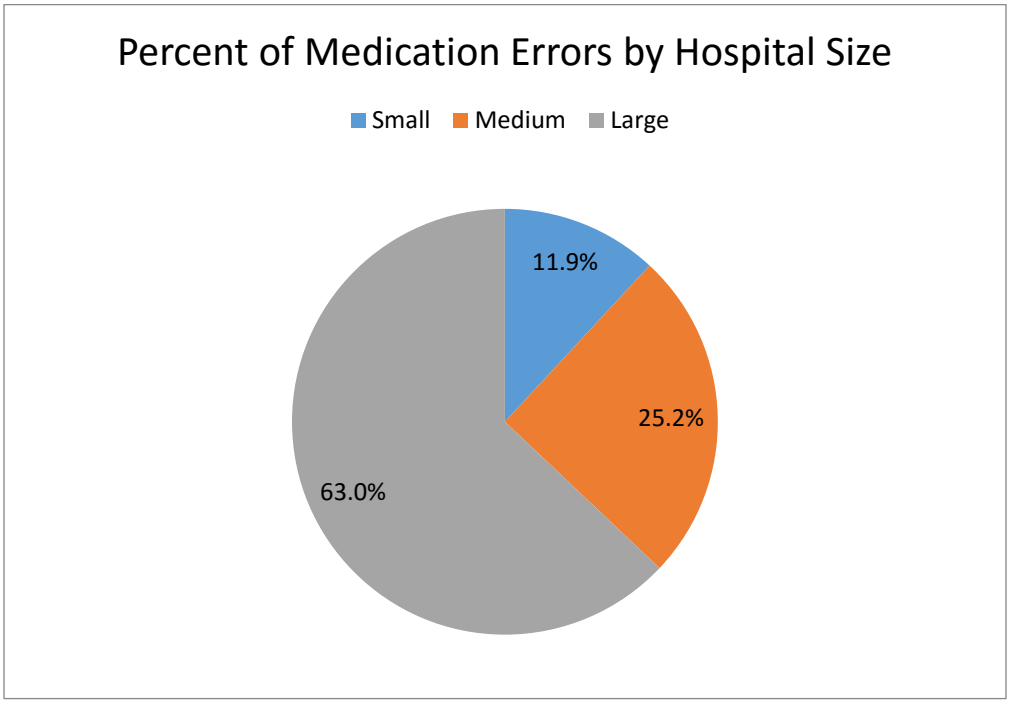


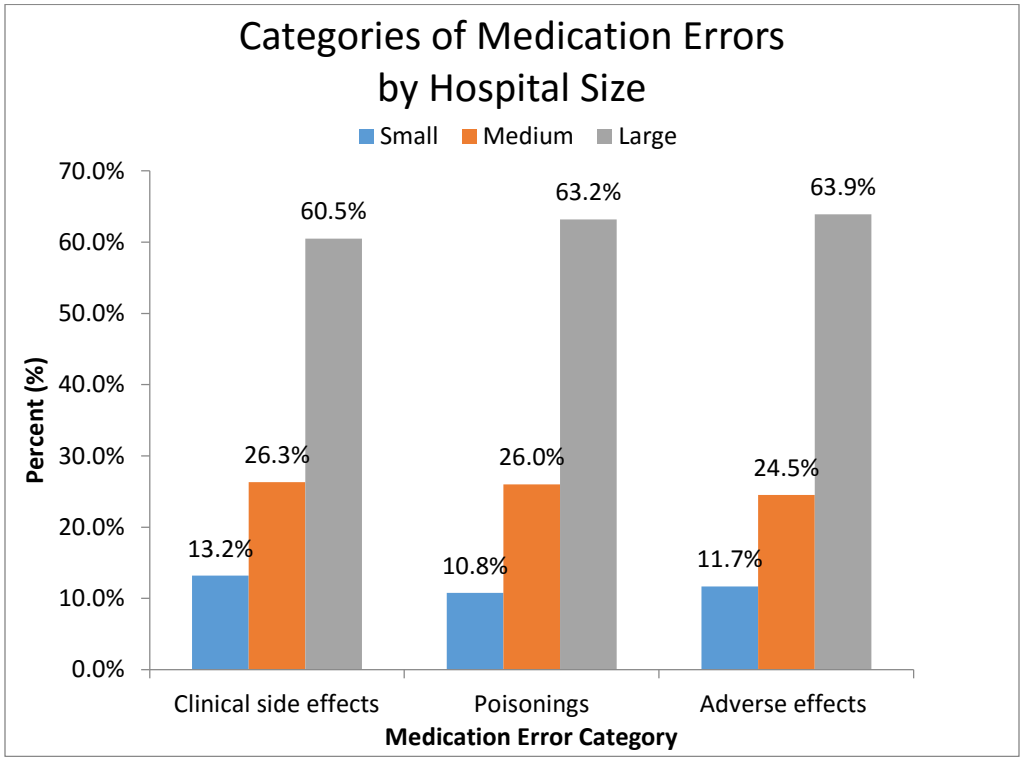
Types of Medication Errors by Primary Insurance Status





Types of Medication Errors by Hospital Size





Types of Medication Errors by Region